Universitat de Lleida

Tourism Surveying from Social Media: The Validity of User-Generated Content (UGC) for the Characterization of Lodging Rankings

Eva Martín Fuentes

http://hdl.handle.net/10803/650336

Universitat de Lleida

TESI DOCTORAL

Tourism Surveying from Social Media: The Validity of User-Generated Content (UGC) for the Characterization of Lodging Rankings

Eva Martín Fuentes

Memòria presentada per optar al grau de Doctor per la Universitat de Lleida
Programa de Doctorat en Enginyeria i Tecnologies de la Informació

Director
Dr Cèsar Fernández Camón

Tutor
Dr Cèsar Fernández Camón

2018
Lleida, Juliol 2018

List of publications resulting from the thesis

Martin-Fuentes, E., Fernandez, C., & Mateu, C. (2018). Does verifying users influence rankings? Analyzing TripAdvisor and Booking.com. *Tourism Analysis: An Interdisciplinary Journal, 23(1),* 1-15. http://doi.org/10.3727/108354218X15143857349459

Martin-Fuentes, E., Mateu, C., & Fernandez, C. (2017). The more the merrier? Number of reviews versus score on TripAdvisor and Booking.com. *International Journal of Hospitality & Tourism Administration.* (Accepted on 27 January 2017. Published online on 29 January 2018). http://doi.org/10.1080/15256480.2018.1429337

Martin-Fuentes, E. (2016). Are guests of the same opinion as the hotel star-rate classification system? *Journal of Hospitality and Tourism Management*, *29*, 126-134. http://doi.org/10.1016/j.jhtm.2016.06.006

Martin-Fuentes, E., Mateu, C., & Fernandez, C. (2018). Are users' ratings on TripAdvisor similar to hotel categories in Europe? *Cuadernos de Turismo.* (Accepted on 22 January 2018).

Martin-Fuentes, E., Fernandez, C., Mateu, C., & Marine-Roig, E. (2018). Modelling a grading scheme for peer-to-peer accommodation: Stars for Airbnb. *International Journal of Hospitality Management*, 69, 75-83. https://doi.org/10.1016/j.ijhm.2017.10.016

Nomenclature

AME	America
ASP	Asia and Pacific
COP	Consumer-Opinion Platform
EUR	Europe
eWOM	Electronic Word of Mouth
Hotrec	Hotels, Restaurants & Cafes in Europe
MEA	Middle East and Africa
P2P	Peer-to-peer
RBF	Radial Basis Function
SVM	Support Vector Machine
UGC	User-Generated Content
WOM	Word of Mouth

Acknowlegments – Agraïments – Agradecimientos

En primer lloc vull agrair el suport del meu director de tesi, el Dr. Cèsar Fernández Camón, pels seus consells, per la seva disponibilitat inmediata, per la seva saviesa amb els Support Vector Machine i que a més d'haver-me guiat i supervisat en aquest camí, li agraeixo tot el que hem rigut plegats.

I would like to thank Dr Jorge Umbelino from the Escola Superior de Hotelaria e Turismo do Estoril for having welcomed me for three months and for having helped me so much with his advices. It was really productive to stay with you in Estoril. Muito obrigada Jorge.

Agradecer al Dr. Santiago Melián y al Dr. Jacques Bulchand de la Universidad de las Palmas de Gran Canaria por sacar tiempo de su agenda para revisar el último artículo y conseguir con sus sugerencias y recomendaciones que el trabajo mejorara notablemente.

També vull agrair el suport dels meus companys del Departament d'Administració d'Empresa de la UdL, a la degana de la Facultat de Dret, Economia i Turisme, M. José Puyalto, i sobretot dels meus companys de grup de recerca en turisme, economia social i del coneixement (TURESCO), gràcies Berta, Eduard, Estela i Natalia. De l'EPS agrair a Ramón que m'hagi inclòs en el seu projecte de recerca i a Luisa pels consells sobre els tràmits a fer per dipositar la tesi.

A mi amiga, Loli, por escuchar mis quejas, emociones, lamentos y satisfacciones y por animarme en todo lo que hago.

A mis hermanas Ana, Esther, Merce y Adriana por los ánimos y esos aplausos en el grupo del WhatsApp cada vez que me aceptaban un artículo.

Als meus nebots Jordi, Pau, Maria i Roger per preguntar-me de tant en tant "i això de la tesi per a què serveix?" "i la tesi quan l'acabes?".

A mis padres, a mi madre que puede ver el trabajo finalizado y a mi padre que hubiera estado muy orgulloso si lo hubiera visto, a ellos por haberme inculcado la importancia del esfuerzo y del trabajo para conseguir lo que una se proponga.

I per últim, el meu millor agraïment és per al Carles, company de viatge infatigable, que encara que no ho vulgui reconèixer, sense el seu suport aquesta tesi no hauria estat possible, per això, i adaptant la dedicatòria de Stephen King a la seva dona Tabitha "This is for Carles, who got me into it - and then bailed me out of it". Gràcies Carles i gràcies Pol per les hores que us he pres.

This thesis has partially funded by the Spanish Ministry of the Economy and Competitiveness: research project TIN2015-71799-C2-2-P and ECO2017-88984-R. This thesis has received a grant for its linguistic revision from the Language Institute of the University of Lleida (2018 call).

The external reviewers of this thesis were Dr Carlos Cardoso Ferreira from University of Lisbon and Dr Emre Ozan Aksöz from Anadolu University.

The Doctoral Thesis Committee was comprised by Dr Jorge Umbelino (president), Dr Carlos Cardoso Ferreira (member) and Dr Ramon Bejar (secretary).

The doctoral thesis was defended on July 18, 2018, obtaining the qualification of Excellent Cum Laude.

Summary

The aim of this research is to determine whether online User-Generated Content (UGC) about the lodging industry validates the ranking system of any accommodation property or platform in order to create an international hotel classification system that may also serve to categorize any type of accommodation.

This thesis presents the work carried out following the collection and analysis of nearly 40 million reviews of hotels worldwide downloaded from TripAdvisor and Booking.com. The choice of these two websites responds to the fact that they are two of the main websites within the tourism sector, one relating to user recommendations that can be reviewed without being verified and the other to an online accommodation booking agency that allows users who are verified to leave reviews about their experiences.

On the one hand, this research focuses on the analysis of information provided by users, and specifically their reviews of accommodation properties, to compare their scores and to determine whether the position of a hotel in both ranking systems – i.e., the recommendation platform where users are not verified and the sales platform where users must be verified to be able to leave a review – is closely related. In addition, the scoring systems of both websites are compared, and it is concluded that each system provides different results for hotels, depending not only on user reviews, but also on the measurement scale of the respective platform.

On the other hand, the research consists of the analysis of hotel classification systems. It demonstrates that although international classification systems are not unified because each country or each region applies its own regulations, there is a relationship between users' ratings and hotel categories worldwide. Consequently, categories can be predicted from UGC on the Internet, among other parameters.

Finally, through machine learning, this thesis creates a model that allows accommodation properties, whether on traditional or collaborative hosting platforms (e.g., Airbnb), to be classified in such a way that different classification systems worldwide are consistent, thereby creating a standard across nations that is easily understandable, that reduces the bureaucracy related to hotel classification systems by eliminating audits, and that aligns users' views with those of the experts who determine the criteria for assigning hotel categories.

Keywords: electronic Word of Mouth (eWOM), User-Generated Content (UGC), hotel classification system

Resumen

El objetivo de esta investigación consiste en determinar si el contenido generado por los usuarios en webs relacionadas con la industria del alojamiento valida los sistemas de clasificación de cualquier establecimiento para crear un mecanismo internacional que pueda servir para categorizar cualquier tipo de alojamiento, incluidos aquellos conocidos como alojamientos de turismo colaborativo.

Esta memoria presenta el trabajo llevado a cabo a través de la descarga y el análisis de cerca de cuarenta millones de reseñas sobre hoteles de todo el mundo descargadas desde TripAdvisor y Booking.com. La elección de estos dos portales responde a que se trata de dos de los principales webs del sector turístico, uno relativo a recomendaciones de usuarios que pueden opinar sin estar verificados y el otro correspondiente a una empresa de intermediación en línea de establecimientos de alojamiento que también permite opinar a los clientes que están verificados sobre su experiencia.

Por un lado, esta investigación se centra en analizar la información brindada por los usuarios con sus valoraciones sobre establecimientos de alojamiento para comparar sus puntuaciones y determinar que la posición que ocupan los hoteles en el ranking está muy relacionada tanto en plataformas de recomendación donde los usuarios no están verificados, como en plataformas de ventas donde los usuarios deben estar verificados para poder opinar sobre su experiencia. Además, se compara el sistema de puntuación de los dos portales para concluir que cada sistema proporciona diferentes resultados a los hoteles, dependiendo no sólo de las revisiones de los usuarios, sino también de la escala de medida de cada plataforma.

Por el otro, la investigación consiste en el análisis de los sistemas de clasificación de hoteles, demostrando que aunque los sistemas de clasificación internacionales no están unificados porqué cada país y cada región aplican sus propias normativas, existe una relación entre las valoraciones generadas por los usuarios y las categorías de hoteles en todo el mundo, de tal manera que las categorías se pueden predecir a partir del contenido generado por los usuarios en internet, entre otros parámetros.

Finalmente, a través de técnicas de aprendizaje automático, esta tesis crea un modelo que permite clasificar los establecimientos de alojamiento ya sean tradicionales o plataformas de alojamiento colaborativo, como Airbnb, para que converjan los diferentes sistemas de clasificación de todo el mundo con el fin de crear un estándar para todas las naciones que sea fácilmente comprensible, que reduzca la burocracia relativa a los sistemas de clasificación hotelera eliminando las auditorías y que haga coincidir el punto de vista de los usuarios con el de los expertos que determinan los criterios para asignar las categorías hoteleras.

Palabras clave: boca a boca digital, contenido generado por el usuario, clasificación hotelera

Resum

L'objectiu d'aquesta investigació consisteix en determinar si el contingut generat pels usuaris en llocs webs relacionats amb la indústria de l'allotjament valida els sistemes de classificació de qualsevol establiment per crear un mecanisme internacional que pugui servir per categoritzar qualsevol tipus d'allotjament, inclosos aquells coneguts com allotjaments de turisme col·laboratiu.

Aquesta memòria presenta el treball dut a terme a través de la descàrrega i l'anàlisi de prop de quaranta milions de ressenyes sobre hotels de tot el món descarregades des de TripAdvisor i Booking.com. L'elecció d'aquests dos portals respon al fet que es tracta de dos dels principals webs del sector turístic, un relatiu a recomanacions d'usuaris que poden opinar sense estar verificats i l'altre corresponent a una empresa d'intermediació en línia d'establiments d'allotjament que també permet opinar sobre la seva experiència als clients que estan verificats.

D’una banda, aquesta investigació se centra en analitzar la informació brindada pels usuaris amb les seves valoracions sobre establiments d'allotjament per comparar les seves puntuacions i determinar que la posició que ocupen els hotels en el rànquing està molt relacionada, tant de plataformes de recomanació on els usuaris no estan verificats com en plataformes de vendes, on els usuaris han d'estar verificats per poder opinar sobre la seva experiència. A més, es compara el sistema de puntuació dels dos portals per concloure que cada sistema proporciona diferents resultats als hotels, depenent no només de les revisions dels usuaris, sinó també de l'escala de mesura de cada plataforma.

De l'altra, la investigació consisteix en l'anàlisi dels sistemes de classificació d'hotels, demostrant que encara que els sistemes de classificació internacionals no estan unificats perquè cada país i cada regió apliquen les seves pròpies normatives, hi ha una relació entre les valoracions generades pels usuaris i les categories d'hotels a tot el món, de tal manera que les categories es poden predir a partir del contingut generat pels usuaris a internet, entre d'altres paràmetres.

Finalment, a través de tècniques d'aprenentatge automàtic, aquesta tesi crea un model que permet classificar els establiments d'allotjament siguin tradicionals o plataformes d'allotjament col·laboratiu, com ara Airbnb, per a què convergeixin els diferents sistemes de classificació de tot el món amb el finalitat de crear un estàndard per a totes les nacions que sigui fàcilment comprensible, que redueixi la burocràcia relativa als sistemes de classificació hotelera eliminant les auditories i que faci coincidir el punt de vista dels usuaris amb el dels experts que determinen els criteris per assignar les categories hoteleres.

Paraules clau: boca a boca digital, contingut generat per l’usuari, classificació hotelera

Table of contents

1. Introduction

An introduction to electronic word of mouth (eWOM) and user-generated content (UGC) in the lodging industry is presented below, followed by the hotel classification systems and a summary of the methodology applied in this thesis.

1.1. Electronic Word of Mouth

The word of mouth (WOM) phenomenon has been widely studied in marketing (Arndt, 1967) and refers to client communications relating to a consumer experience (Anderson, 1998). WOM, propagated via the Internet, is known as ‘electronic word of mouth’ (eWOM) (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004) and, according to the most cited definition, eWOM is “all informal communications directed at consumers through Internet-based technology related to the usage or characteristics of particular goods and services, or their sellers” (Litvin, Goldsmith, & Pan, 2008, p. 461).

Online consumer reviews of goods and services have become increasingly important because they influence other consumers (Boyd, Clarke, & Spekman, 2014) and help consumer decision-making (Dellarocas, Zhang, & Awad, 2007; Xiang, Du, Ma, & Fan, 2017). Users have become more empowered as a result of the development of social media. Indeed, consumers have become active agents (Hvass & Munar, 2012; Munar, 2011; Sigala, Christou, & Gretzel, 2012) who generate content and influence one another (Marine-Roig, Martin-Fuentes, & Daries-Ramon, 2017).

Social media enable UGC, which has grown exponentially in recent years and has transformed the tourism industry (Buhalis & Law, 2008). Travel-related UGC is becoming more widespread (Leung, Bai, & Erdem, 2017) and is an invaluable source of information not only for travelers, but also for academic researchers (Kwok, Xie, & Richards, 2017). In addition, users’ reviews provide hotel managers with information to enable them to take steps to improve the services offered (Cantallops & Salvi, 2014).

There are several platforms where users give their opinions about their travel experiences, which can be divided into advice and sales websites (Fernández-Barcala, González-Díaz, & Prieto-Rodríguez, 2010). These platforms allow users to share information and experiences, from community-based sites or from transaction-based online travel agencies (OTAs) (Xiang, Du, Ma, & Fan, 2017).

Within the tourism sector, there are several community-based platforms where independent travelers share information about destinations, things to do, hotels, restaurants, etc., such as TripAdvisor, Minube, Lonely Planet’s Thorn Tree, WAYN, and Travellerspoint.

Undoubtedly, the platform par excellence for sharing travel information is currently TripAdvisor, since it is one of the most influential eWOM sources within the hospitality and tourism context (Baka, 2016; Yen & Tang, 2015).

TripAdvisor is the world's largest travel site, with over 570 million reviews, a community of 455 million average monthly visitors, covering 7.3 million accommodations, airlines, attractions, and restaurants and operating in 49 markets worldwide (TripAdvisor, 2018).

Additionally, there are companies that provide lodging in hotels and vacation rentals (Booking.com, Ctrip, FlipKey, Niumba, etc.) or even in private properties (Airbnb, HomeAway, and so on) that allow consumers who have booked through their platform to share their experiences (Gligorijevic, 2016).

Nowadays, one of the most important and popular OTA's is Booking.com which is an online accommodation booking website. It claims to have 1,593,804 properties in 230 countries and to deal with over 1.5 million room-night reservations per day. Booking.com B.V. is based in Amsterdam in the Netherlands and is owned and operated by United States-based Priceline. It is supported internationally by 198 offices in over 70 countries (Booking.com, 2018).

The information provided by these websites is very valuable for research into tourism, as evidenced by the numerous studies that have been based on data provided by TripAdvisor (Xiang et al., 2017). Travel intermediary websites such as Booking.com are also a popular online source of hotel information, as are social media websites like TripAdvisor and Facebook (Sun, Fong, Law, & Luk, 2015).

1.2. Hotel classification systems

In travel and hospitality, online reviews have increased exponentially and there is usually a huge number of reviews available for the same product or service (De Ascaniis & Gretzel, 2012). However, a massive amount of information can be both positive and negative (O'Connor, 2010) because information overload may complicate the decision-making process (Fang, Ye, Kucukusta, & Law, 2016; Marine-Roig, 2017).

To simplify tourists' decision-making related to the accommodation industry, hotel categories are a useful tool for filtering information and preventing online information overload from UGC (Blomberg-Nygard & Anderson, 2016) and from recommender systems (Zhou, Xu, Li, Josang, & Cox, 2012).

Although the star-rating classification mechanism does not follow the same pattern worldwide because systems are not unified, hotel categories are the most common customer segmentation pattern in the hotel industry (Dioko, So, & Harrill, 2013).

Apart from mitigating information overload, third-party certifications are useful for avoiding information asymmetries (Nicolau, & Sellers, 2010) as well as eWOM that also serves to avoid information asymmetries in hotel industry (Manes & Tchetchik, 2018). Hotel classification systems should also be refined by integrating online reviews because both play complementary roles (Blomberg-Nygard & Anderson, 2016).

In this respect, hotel classification systems are established using various standards set by governments or by independent organizations. These systems are universally recognized, and the most common method for classifying hotels is to rank them from 1 to 5 stars although levels may be different (e.g., Malta, from 2 to 5 stars). Symbols other than stars are also used, such as diamonds and crowns.

There is an initiative by hotel associations from some European countries, sponsored by the Hotrec Association (Hotels, Restaurants & Cafes in Europe), that is trying to implement a scoring system to enable the unification of criteria for the allocation of stars in different countries (Hotrec, 2015), but it is not so easy because, even within a single country, there are different systems in place. This is the case for Spain, which has so many different classification systems, as the regional governments have the powers to regulate in this field.

The majority of the legislation in Spain regulates certain indispensable requirements that must be met to get a given category, such as minimum floor space in rooms and common areas, services and basic infrastructures (elevator, telephone, air-conditioning) among others; and a system that assign points to get a better category depending on the achievement of certain items (room service, staff elevator, parking for buses, direct communication service between the room and the reception, and so on).

With the idea of seeking tighter integration between online reviews and hotel classification systems, and after a review of the literature, we realized that there was a need to create an international hotel classification system that merged UGC with the categories, which would be valid for classifying not only hotels, but also any type of accommodation. A system that would harmonize most of the classification systems worldwide, that would be easily understood by all, that would mitigate information asymmetry, that would not use obsolete criteria, that would always be up to date, that would avoid information overload, and that would allow it and official systems to converge.

Before, however, it was necessary to validate whether UGC and the international hotel classification system were consistent. This was done by first analyzing UGC on two of the lodging industry’s most popular websites, one from a community-based site on which users are able to post reviews without being verified (TripAdvisor) and one from the transaction-based OTA on which guests are only able to leave comments about their experience after booking a room through the OTA, and only after receiving an invitation to do so by e-mail (therefore being verified) (Booking.com).

To carry out this task, it was necessary to download, process and analyze the data from TripAdvisor and Booking.com.

1.3. Data collection, data processing and statistical model

This section shows the data selection, the process for downloading the data, and the statistical procedure developed later to process the data obtained.

1.3.1. Data collection

According to Xiang, Schwartz, Gerdes, & Uysal, (2015), the analysis of big data is a major challenge in research. However, as those authors pointed out, there are not many applications in the hospitality sector that explore the possibilities offered by big data. This research therefore uses big data downloaded from Internet that would have been impossible to obtain by means of survey-based studies.

The sample was taken from data available on TripAdvisor and on Booking.com, the two websites selected because of their importance, as mentioned previously.

As the most widespread and popular form of accommodation on Booking.com, hotels were chosen in order to obtain as much data as possible for the comparison between Booking.com and TripAdvisor.

We chose hotels from the top destinations in the world according to the TripAdvisor Ranking 2015 and from the Top 100 city tourist destinations in the world according to the Euromonitor Ranking (Geerts, 2016). We divided them into four regions, as proposed by Banerjee & Chua (2016): America (AME), Asia and Pacific (ASP), Europe (EUR) and the Middle East and Africa (MEA). We then split these regions into countries and cities, in order to obtain more accurate results from a geographical point of view.

The data were downloaded at different times between November 2015 and August 2016 using an automatically controlled web browser, developed in Python, that simulated user navigation (clicks and selections) for TripAdvisor and Booking.com.

We automatically gathered the rankings of the hotels on Booking.com and TripAdvisor: the number of reviews, the ranking and scoring, the hotel name, city and country. The variables hotel category, number of rooms and room price were downloaded from Booking.com.

In order to download the data, a webscraping tool was built, using a library to devise it (Python's Scrapy).

1.3.2. Data preprocessing

Once the data had been downloaded and we had at our disposal a dataset with data from both sites (Booking.com and TripAdvisor), we created a new dataset by combining the data for each given hotel from both websites. The criteria used to combine two records were:

- If the hotel name on both origin datasets matched exactly, we considered that it was the same hotel.
- Else if the hotel name from one site was contained entirely in the name from the other site (the choice of container and content depended on name length, the longest name was chosen as a candidate container and the shortest as a candidate content).
    - For example, shown below are two candidates:
      Booking.com: Le 123 Elysees – Astotel
      TripAdvisor: Hotel Le 123 Elysees – Astotel
      Both candidates obviously refer to the same hotel, as the name from Booking.com is entirely contained within the name from TripAdvisor.

- For all the unmatched hotels, the Ratcliff/Obershelp similarity (Ratcliff & Metzener, 1988) was computed between each possible pair of names (one from Booking.com and one from TripAdvisor). This list of distances was then sorted, and the largest one (best match) was chosen. If that similarity was higher than 0.85 (that is 85% of letters of each side match considering the position of the letter), the pair was chosen as a match, and the names removed from both origin lists.
    - For example, this pair in the same city:
      Booking.com: Campanile Hotel Wakefield
      TripAdvisor: Campanile Wakefield
      Have a Ratcliff/Obershelp similarity of: 0.8636, and they will be matched accordingly.

That algorithm was used on a city basis, which reduced the possibility of errors, i.e., combining two different hotels with the same name but in different cities as one, and also helped speed up the process.

For this reason, the datasets downloaded from TripAdvisor and Booking.com separately contained more elements than the combined one, as there where hotels not contained in both sites, i.e., those for which a suitable match could not be found.

1.3.3. Statistical method

The collected data were exported to a CSV file, which allowed it to be analyzed. The statistical calculations were performed using R version 3.2.1 software. R is the leading tool for statistics, data analysis, and machine learning. It is more than a statistical package; it is a programming language, so you can create your own objects, functions, and packages. Moreover, R software makes it easy to reproduce and update analysis because R documents the steps of the analysis.

Another reason for choosing R is that it is open source, with a policy of code transparency that enables auditable and reproducible research (Ince, Hatton, & Graham-Cumming, 2012).

Depending on the aim of each article, different statistical calculations were performed. The statistical analysis performed in chapters 4 to 7 were Pearson's correlation, Spearman's correlation (to analyze ordinal variables), Chi square, linear regression models, Student's t-distribution or ANOVA tests, depending on the data and on the analysis being performed.

In chapter 8, machine learning was performed. This specifically entailed a technique called Support Vector Machines (SVMs) as a supervised learning model of classification. The supervised learning task used a training dataset and learned known classifications (hotel categories) based on a range of different parameters (price, reviews, score, wish list, etc.) in order to correctly determine the class for the instances (hotels), in other words, the supervised learning algorithm predicted a classification that could be applied later on to new instances.

2. Aim and objectives of the thesis

This section is dedicated to the aim and objectives of this thesis as a whole. The aim of the thesis is to determine whether online User-Generated Content (UGC) within the lodging industry validates the ranking system of any accommodation property or platform in order to create an international hotel classification system that could categorize any type of accommodation based on different variables.

To achieve this goal, the research was divided into two main parts. The first part consisted of the analysis of information provided by users in their reviews of lodging properties to compare their scores on recommendation platforms where users are not verified and on sales platforms where users must be verified to leave reviews about their experiences. Moreover, in this part, we compared the evaluation systems of both websites (recommendation versus sales platforms) to determine whether each system provided different results for the hotels, depending not only on user scores, but also on the measurement scale.

The second part consisted of the analysis of the hotel classification systems to demonstrate that although international classification systems are not unified because each country or region applies its own regulations, there is a relationship between UGC and hotel categories worldwide. Consequently, hotel categories could be predicted from features generated specially by users through their online travel reviews, among other parameters. Furthermore, this part also consisted of modeling a grading scheme for application to peer-to-peer (P2P) accommodation platforms that could be easily understood worldwide.

Thus, the validity of UGC for the characterization of lodging rankings could be demonstrated, regardless of the type of property, and the model could even be applied in the future to any other element that users could potentially comment on and rate.

In order to achieve this aim, applied to the lodging industry, the research objectives were:

- To review the state-of-the-art of eWOM and UGC with regard to lodging websites, both sales and recommendation websites.
- To compare the behavior of user-generated ratings, online reviews, and measurement scales on two of the most popular tourism platforms.
- To predict the international hotel categories with UGC and other features, considering that the hotel classification system is not unified because each country or region applies its own regulations.
- To create a model to classify the properties offered by P2P accommodation platforms based on user interaction, similar to grading scheme categories for hotels.

3. Structure of the thesis

This thesis is presented as a compendium of five articles: one published in a Q1 journal as classified by Science Citation Index (SCI), three published in a Q2 journal as classified by Scimago Journal Rank (SJR), and one accepted by (but yet to be published in at the time of writing) a Q3 journal as classified by SJR and included in the Emerging Sources Citation Index (ESCI).

In this regard, Chapter 1 is an introductory section of this thesis. In this chapter, an overview of social media, eWOM, UGC, and hotel classification categories is provided. Moreover, data collection, data analysis and the methods used are explained.

The aim and objectives of this thesis are presented in Chapter 2 and the entire scheme of the doctoral thesis is provided in Chapter 3.

Chapter 4 corresponds to the first article, which compiled a literature review on eWOM as an introduction to the topic, having firstly noted the importance and popularity of TripAdvisor in tourism and hospitality UGC research, and secondly that it is an extraordinary source of data for tourists, hoteliers, managers and researchers. Booking.com is also an important data source in tourism research although the number of studies using this source is lower than those using TripAdvisor. For this reason, and in light of the criticism leveled at TripAdvisor about the lack of user verification, the first article was written to compare both rankings, complementing it with a comparison of the measurement scales of both websites, especially given the unique scale of Booking.com.

There is vast scholarly literature on the quantity of user reviews, with particular interest in the influence that the volume of reviews has on the score obtained by hotels. For that reason, Chapter 5 corresponds to the second article in which a comparison between the two platforms is made to conclude that the results depend on the management of each website.

Chapter 6 corresponds to the article that confirms that there are significant differences in the score results depending on the hotel category. The relationships between users' ratings on TripAdvisor and Booking.com and other parameters were analyzed, and it was confirmed that UGC does indeed validate the hotel classification systems at an international level.

In chapter 7 (the fourth article, in the review stage at the time of writing), a comparison of ratings and hotel categories is performed on all hotels listed on TripAdvisor from nine European countries.

In chapter 8 (the last paper), the possibility of predicting the hotel categories worldwide with UGC and other features by using machine learning techniques was established. After this finding, the same methodology was applied to lodging properties of the so-called 'sharing economy' and it was found that it is indeed possible to establish a ranking system from UGC and other parameters that is easily understood worldwide for this type of accommodation.

In chapter 9 and 10 the discussion and conclusions as a whole are presented and Chapter 11 shows other research activities research carried out during the doctoral program. The thesis is completed with a compilation of all the references.

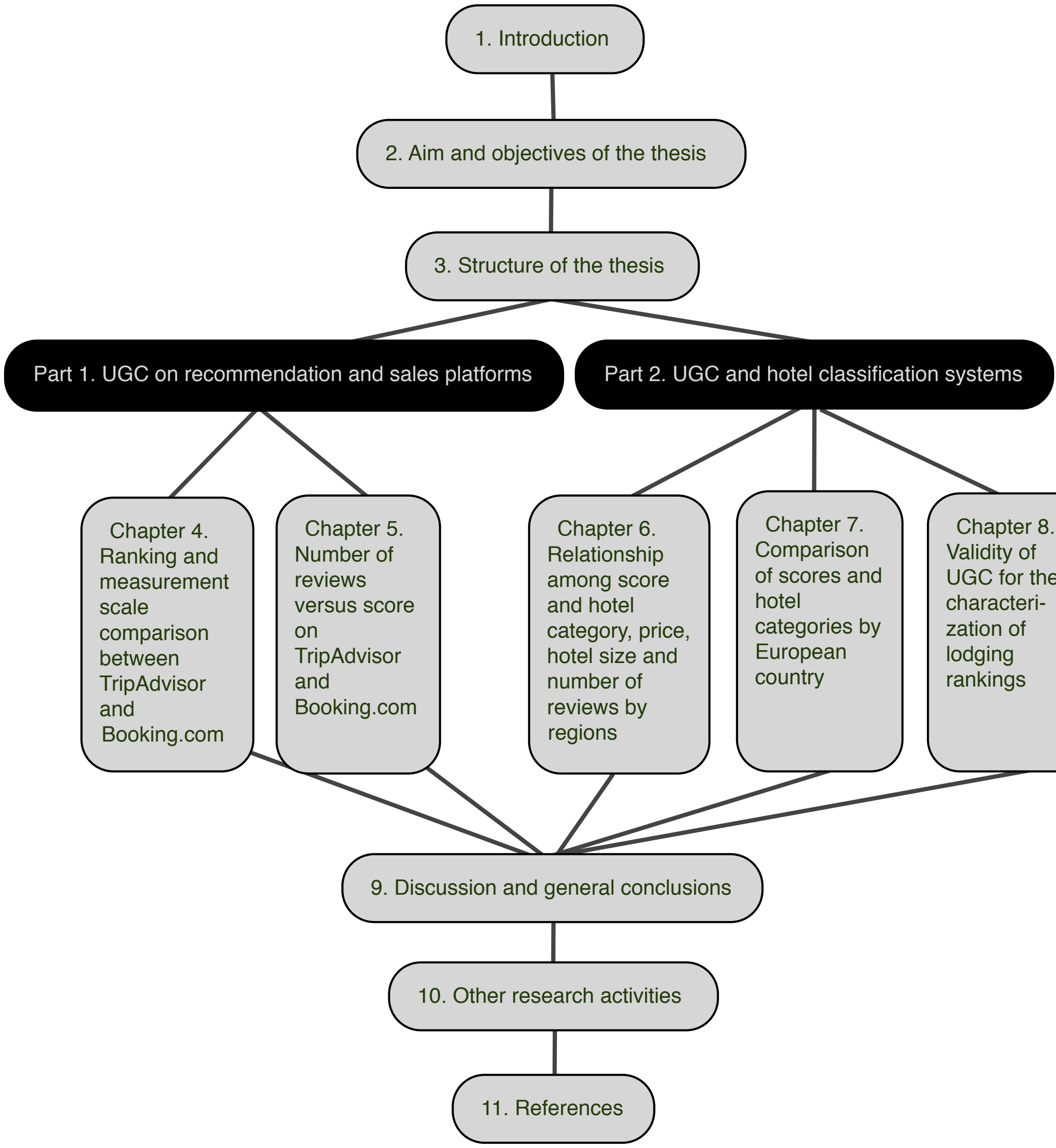


Figure 1: Structure of the thesis

4. Does verifying users influence rankings? Analyzing TripAdvisor and Booking.com

Pages 11 to 46 contain this article:

Martin-Fuentes, E., Fernandez, C., & Mateu, C. (2018). Does verifying users influence rankings? Analyzing TripAdvisor and Booking.com. *Tourism Analysis: An Interdisciplinary Journal, 23(1),* 1-15. http://doi.org/10.3727/108354218X15143857349459

Journal Metrics

SCImago Journal Rank (SJR): 0.474

Year 2017 Second Quartile

Area: Business, Management and Accounting. Rank 475 of 1,605

Subject area: Tourism, Leisure and Hospitality Management. Rank 44 of 101

Tourism Analysis, Vol. 23, pp. 1–15
Printed in the USA.

1083-5423/18 $60.00 + .00
DOI: https://doi.org/10.3727/108354218X15143857349459
E-ISSN 1943-3999
www.cognizantcommunication.com

DOES VERIFYING USES INFLUENCE RANKINGS? ANALYZING BOOKING.COM AND TRIPADVISOR

EVA MARTIN-FUENTES,* CARLES MATEU,† AND CESAR FERNANDEZ†

*Department of Business Administration, University of Lleida. Lleida, Spain
†INSPIRES Research Institut, University of Lleida, Lleida, Spain

Electronic word of mouth (eWOM) is of recent and considerable importance in tourism, particularly because of the intangible nature of the industry. Users' online reviews are a source of information for other consumers, who take them into account before making a reservation at a lodging property. The aim of this study is to establish whether or not the anonymity of the reviews on TripAdvisor alters hotel rankings by comparing them with verified users' reviews on Booking.com. Moreover, the study analyzes whether or not the differences in the rating scales of both websites favor some hotels over others. A large amount of data is used in this study, with more than 40,000 hotels on Booking.com and 70,000 on TripAdvisor in 447 cities around the world, comparing the rankings of about 20,000 hotels matched on both websites. Our findings suggest that the behavior of both rankings is similar and the lack of veracity on TripAdvisor due to the anonymity in the user's verification system is baseless. In addition, some differences are found depending on the hotel category and region, due mainly to the unique rating scale on Booking.com (from 2.5 to 10) compared with the rating scale on TripAdvisor (from 1 to 5).

Key words: Electronic word of mouth (eWOM); TripAdvisor; Booking.com; Ranking; Rating scale

4.1. Introduction

Since its creation, TripAdvisor has had its share of controversy and has been widely questioned to the point of going to court over allegations by managers from hospitality establishments that feel harmed by it (Grindlinger, 2012). The main criticism of this platform is the perceived lack of veracity (Palmer, 2013; Rawlinson, 2011; Smith, 2012). Hoteliers complain about the anonymity of TripAdvisor; they argue the site allows anonymous users to give opinions about any establishment without having stayed there or used it (Webb, 2014).

Conversely, Booking.com is a hotel-booking website that allows comments to be made by customers. The site claims that it publishes "verified reviews from real people" because leaving a review on this website is only possible if an individual books an accommodation through the site and actually stays at the reviewed property.

The aim of this study is to establish whether or not the anonymity of the reviews on TripAdvisor alters hotel rankings by comparing them with verified users' reviews on Booking.com.

Alternatively, a study about the effects of the Booking.com scoring system has confirmed suspicions of "inflated scores" derived from their scoring system (Mellinas, Martínez, & Bernal García, 2016). This research also aims to confirm whether or not the differences in the rating scales of both websites favor some hotels over others.

4.2. Contribution to the state-of-the-art

The most important finding of this paper is that, for most of the cities analyzed, there is a high degree of relationship between both websites' rankings (Booking.com and TripAdvisor). They likewise show that the possible posting of fake reviews on TripAdvisor does not seem to be prevalent, as both rankings behave similarly. After comparing TripAdvisor to Booking.com, suspicions of fraud on TripAdvisor because of its unverified user reviews were not borne out. As the number of reviews grows, the impact of possible fake reviews falls, as they are overwhelmed by genuine UGC thanks to the tendency of human behavior to embrace "the power of the crowd".

The unique rating scale of Booking.com (from 2.5 to 10) compared to TripAdvisor's scale (from 1 to 5) was found to be beneficial to 1- to 3-star hotels in America and Europe, and detrimental to 5-star hotels worldwide and to 4-star hotels in Asia and Pacific and Middle East and Africa.

4.3. Journal paper

Does verifying users influence rankings? Analyzing TripAdvisor and Booking.com

Eva Martin-Fuentes*[a], Carles Mateu[b], Cesar Fernandez[b]

University of Lleida

[a] Department of Business Administration.

E-mail: eva@aegern.udl.cat

University of Lleida. C/ Jaume II, 73, 25001 LLEIDA, Spain.

Telephone number: + 34 973 703216

[b] INSPIRES Research Institute.
E-mail: carlesm@diei.udl.cat cesar@diei.udl.cat

University of Lleida. C/ Jaume II, 69, 25001 LLEIDA, Spain.

Telephone number: + 34 973 702199

*corresponding author

Abstract

Electronic word of mouth (eWOM) is of recent and considerable importance in tourism, particularly because of the intangible nature of this industry. Users' online reviews are a source of information for other consumers, who take them into account before making a reservation at a lodging property.

The aim of this study is to establish whether or not the anonymity of the reviews on TripAdvisor alters hotel rankings by comparing them with verified users' reviews on Booking.com. Moreover, the study analyzes whether or not the differences in the rating scales of both websites favor some hotels over others.

Big data is used in this study, with more than 40,000 hotels on Booking.com and 70,000 on TripAdvisor in 447 cities around the world, and compares the rankings of about 20,000 hotels matched on both websites.

Our findings suggest that the behavior of both rankings is similar and the lack of veracity on TripAdvisor due to the anonymity in the user's verification system is baseless. In addition, some differences are found depending on the hotel category and region, due mainly to the unique rating scale on Booking.com (from 2.5 to 10), as compared to the rating scale on TripAdvisor (from 1 to 5).

Keywords: eWOM, TripAdvisor, Booking.com, ranking, big data, rating scale

1. Introduction

Since its creation, TripAdvisor, a travel information website whose content is provided mostly by users, has had its share of controversy and has been widely questioned to the point of going to court over allegations by managers from hospitality establishments that feel harmed by it (Grindlinger, 2012).

The main criticism of this platform is the perceived lack of veracity (Palmer, 2013; Rawlinson, 2011; Smith, 2012). Hoteliers complain about the anonymity of TripAdvisor; they argue the site allows anonymous users to give opinions about any establishment without having stayed there or used it (Webb, 2014).

Conversely, Booking.com is a hotel-booking website that allows comments to be made by customers. The site claims that it publishes "verified reviews from real people" because leaving a review on this website is only possible if an individual books an accommodation through the site and actually stays at the reviewed property.

These two websites are significant in the tourism sector and to the online reputation of the accommodation facilities reviewed. They are also important in terms of the research done before making a reservation –the percentage of which continues to rise (Anderson, 2012)– because consumer reviews generate more confidence than communications from the company (Gretzel & Yoo, 2008; Vermeulen & Seegers, 2009).

Moreover, being number one in a ranking is something to which every business aspires because potential customers see the top positions first (Spink & Jansen, 2006). A higher position results in a decision to use either tourism products (Ghose, Ipeirotis, & Li, 2012) or any other type of product (Pope, 2009; Sorensen, 2007), which therefore leads to more bookings (Ye, Law, Gu, & Chen, 2011). According to Filieri and McLeay (2013), product ranking emerges as the strongest antecedent of high-involvement travelers' adoption of information from online reviews.

The aim of this study is to establish whether or not the anonymity of the reviews on TripAdvisor alters hotel rankings by comparing them with the verified users' reviews on Booking.com. Alternatively, a study about the effects of the Booking.com scoring system confirms suspicions of "inflated scores" derived from their scoring system (Mellinas, Martínez, & Bernal García, 2016).

Taking into account that the scoring scale on Booking.com is from 2.5 to 10 and on TripAdvisor from 1 to 5, —keeping in mind the research gap Mellinas et al., (2016) present about the interest in performing similar studies with different samples and selecting hotels from other countries— the study seeks to compare whether or not the differences in the scales favor some hotels by their category and location over others.

Although eWOM for tourism is widely studied, the validity of anonymous reviews receives little attention. This article tries to fill this gap and helps incorporate research with the validity of reviews posted without verification procedures. Moreover, this article tries to provide additional insight into the effects of the Booking.com scoring system, complementing that of Mellinas et al., (2016) by analyzing a large volume of data from hotels worldwide and not just from a single country, comparing scores on “sale websites” (Booking.com) and “advice websites” (TripAdvisor) (Fernández-Barcala, González-Díaz, & Prieto-Rodríguez, 2010), and comparing the behavior of the scales according to the hotel categories.

2. Theoretical background and study hypotheses

2.1. Word of mouth

The word of mouth (WOM) phenomenon is studied in marketing (Arndt, 1967) and refers to client communications relating to a consumer experience (Anderson, 1998). With the advent of the internet, the way in which WOM reviews are made has been extended thanks to consumer-opinion portals (COPs) (Burton & Khammash, 2010), which allow consumers to review products and services and other people to view these online reviews and contribute to attenuating the negative effects of asymmetric information (Martin-Fuentes, 2016). WOM, propagated via Web 2.0, is known as 'electronic word of mouth' (eWOM) (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004) and is defined as "all informal communications directed at consumers through Internet-based technology related to the usage or characteristics of particular goods and services, or their sellers" (Litvin, Goldsmith, & Pan, 2008: 461) and it has implications for tourism marketing (Morosan, 2013).

Recent eWOM studies have been conducted in relation to goods and services (Chevalier & Mayzlin, 2006; Cheung & Thadani, 2012). According to Cantallops and Salvi, (2014), those focusing on the hotel industry can be split into review-generating factors (previous factors that encourage consumers to write reviews) and eWOM impacts (impacts caused by online reviews) from the point of view of consumers and companies.

Research based on fifty articles about hospitality and tourism eWOM concludes that "online reviews appear to be a strategic tool that plays an important role in hospitality and tourism management, especially in promotion, online sales, and reputation management" (Schuckert, Liu, & Law, 2015: 618).

TripAdvisor is one of the most influential eWOM sources in the context of hospitality and tourism (Yen & Tang, 2015), and it is often a hotel manager's first point of call because of the significance the site has acquired for any accommodation facilities' reputation (Xie, Zhang, & Zhang, 2014). TripAdvisor is ranked as the most reliable source according to the perceptions of general managers (Torres, Adler, & Behnke, 2014). Numerous studies have been based on data provided by TripAdvisor (Ayeh, Au, & Law, 2013; Liu, Pennington-Gray, Donohoe, & Omodior, 2015; Mayzlin, Dover, & Chevalier, 2012; Melian-Gonzalez, Bulchand-Gidumal, & Gonzalez Lopez-Valcarcel, 2013; O'Connor, 2008; Vermeulen & Seegers, 2009). The percentage of consumers who consult TripAdvisor before booking a hotel room continues too increase (Anderson, 2012) and online rating lists are more useful and credible when published by well-known online travel communities like TripAdvisor (Casaló, Flavián, Guinalíu, & Ekinci, 2015).

In TripAdvisor's own words, it "is the world's largest travel site, enabling travelers to plan and book a trip". TripAdvisor branded sites make up the largest travel community in the world, reaching 350 million unique monthly visitors, with more than 320 million reviews and opinions covering more than 6.2 million accommodations, restaurants and attractions (TripAdvisor, 2016a). However, TripAdvisor's fame is also accompanied by some criticism because of the opportunity to comment anonymously without needing to have enjoyed the services of the hospitality industry (Gerrard, 2012); cases of a lack of truthfulness have been reported by journalists (Palmer, 2013; Rawlinson, 2011; Smith, 2012), as have cases of blackmail (Morrison, 2012; Webb, 2014). For example, some customers have tried to force establishment owners to offer a discount or invite them stay another day by telling owners they would leave negative comments on social websites if their demands were not met.

Booking.com is an online accommodation-booking website where travelers can compare prices and customer reviews (Neirotti, Raguseo, & Paolucci, 2016). The site claims to have 895,589 properties in 224 countries and to deal with over 1 million room-night reservations per day (Booking.com, 2016). Travel intermediary websites such as Booking.com are a popular online source for hotel information, as are social media websites like TripAdvisor and Facebook (Sun, Fong, Law, & Luk, 2015) which draw the attention of researchers (Balagué, Martin-Fuentes, & Gómez, 2016; Viglia, Minazzi, & Buhalis, 2016).

2.2. Anonymity

It is possible for user-generated content to be anonymous because during the registration process on a COPs, identities can be invented. This anonymity leads some reviewers to question the authenticity of the ratings posted on TripAdvisor (O'Connor, 2008) or discount their credibility (Duan, Gu, & Whinston, 2008). Moreover, anonymous users can post fake reviews to increase the reputation of their businesses or to harm their competitors (Dellarocas, 2003). Consumers often perceive eWOM as less trustworthy than WOM because it is difficult to identify the issuer, since UGC is often created anonymously (Sparks & Browning, 2011; Yoo & Gretzel, 2010 cited by Leung, Law, van Hoof, & Buhalis, 2013).

As explained previously, to post a review on TripAdvisor there is no need to demonstrate that a user has actually stayed at a hotel; thus, the biggest threat to TripAdvisor is a loss of credibility (O'Connor, 2008). This fact is not the case with Booking.com because after booking a room through this website and staying at the accommodation, the customer receives an invitation via e-mail to write a comment about the experience. So Booking.com only publishes reviews from users who have booked at least one night at a lodging property through its website and then stayed there. They therefore guarantee that the opinion is real —of which the system is aware.

2.3. Rankings

Rankings are used to quickly compare different options, thereby reducing the information time. If we consider that travelers economize on time and effort when they search for information (Solomon, Russell-Bennett, & Previte, 2012 cited by Filieri & McLeay, 2013) then rankings are a good way to obtain information on any kind of product or service.

Different studies show that rankings can have a significant impact on the decision to purchase a product or service. Among the different studies, worthy of note include Sorensen (2007) on the impact of the New York Times Best Sellers List on sales, that of Jin & Whalley, (2007) on how rankings affect the financial resources of public colleges, and that of Pope (2009) on the U.S. News & World Report ranking and its importance in the choice of hospitals in the United States.

As confirmed by Filieri and McLeay (2013), product ranking is now the strongest antecedent of high-involvement travelers' adoption of information from online reviews.

Taking into account that most users' internet search engines only look at the first three pages of results (Spink & Jansen, 2006), that search results on Google decrease depending on their position in the ranking (Chitika, 2013), and that users rarely read reviews beyond the first web page (Pavlou & Dimoka, 2006), rankings are a highly valuable source of information and ranking in the top positions can draw the attention of potential customers.

Therefore, we propose the following hypothesis:

H1 Hotel rankings on TripAdvisor and Booking.com are related although they have different verification systems.

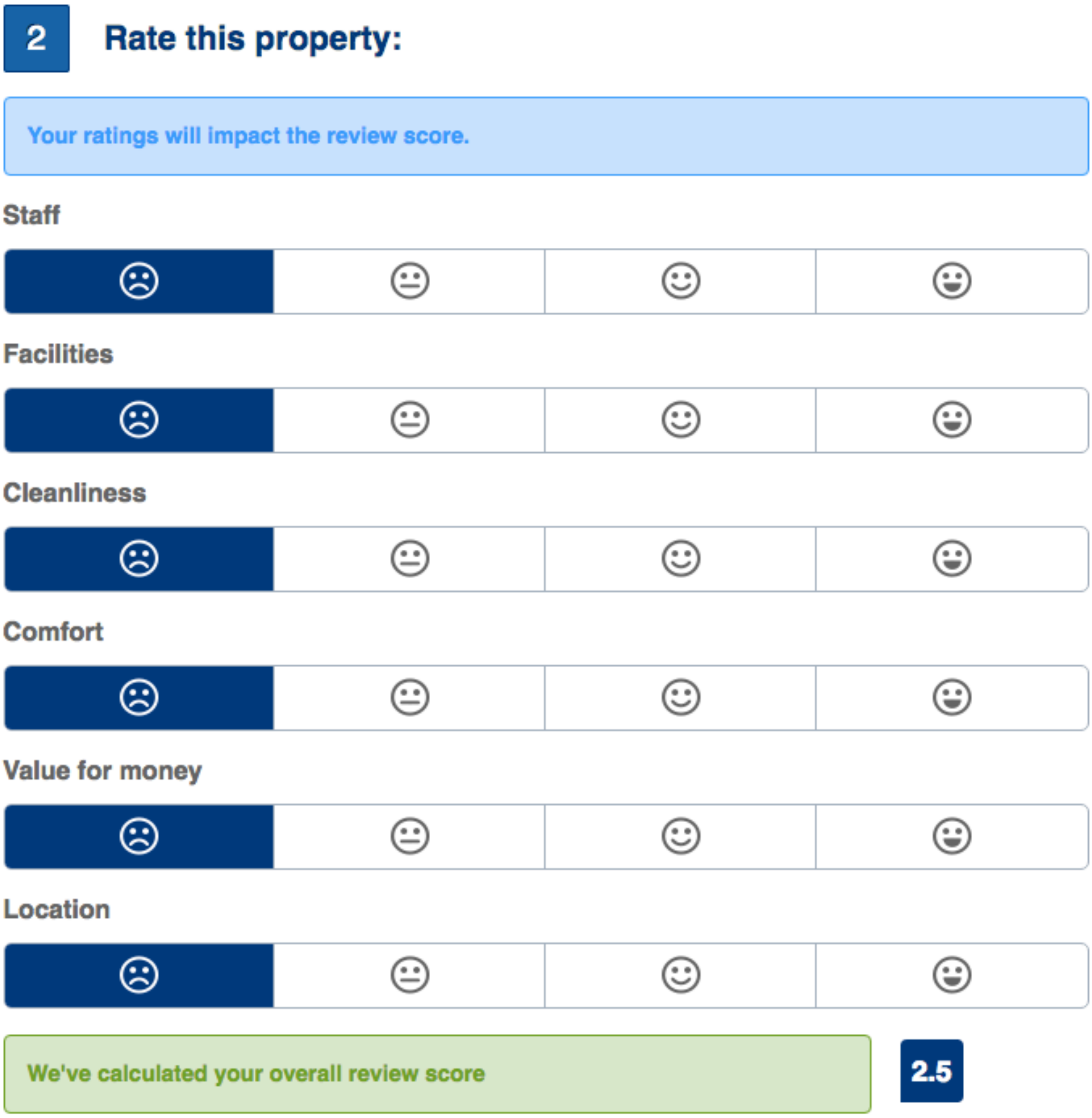
2.4. Rating scales on Booking.com and TripAdvisor

Because of the importance of Booking.com and TripAdvisor to the hospitality sector, there are many studies using these two websites based on user-generated content (UGC) for hotel experiences through content analysis techniques (Barreda & Bilgihan, 2013), or the analysis of reviews on each site with 50 hotels from Portugal (Chaves, Gomes, & Pedron, 2012).

The hotel scoring scale used by Booking.com is from 2.5 to 10 as shown in Figure 1 and as confirmed by Mellinas, Martínez María-Dolores, & Bernal García, (2015). Meanwhile, the scoring scale used by TripAdvisor is from 1 to 5, rounding decimals to the midpoint.

Mellinas et al., (2015) conclude that this scale explains why most hotels have ratings above 7 and point out a research gap in the necessity to study the effects of this scoring system by quantifying how it inflates values.

Figure 1. Form sent by Booking.com to rate accommodation



Source: Booking.com

Bjørkelund, Burnett, & Nørvåg, (2012) compare hotels on TripAdvisor and on Booking.com. From a set of more than 600,000 reviews on Booking.com, they find that none are lower than 2.5 and conclude that Booking.com scores lean toward the higher end of the scale more often than TripAdvisor.

Mellinas et al., (2016) compare hotel scores between Booking.com and Priceline and assert that there is no mean equality of scores, and that there are very significant differences (in favor of Booking.com) for hotels with low scores, low differences in average-rated hotels and an absence of differences for hotels with high scores. Hotels with a very high scores on Priceline have a weak superiority of scores.

Taking into account the limited literature on the unique rating scale of Booking.com, the following hypothesis is proposed:

H2 The rating scale on Booking.com (2.5-10) generates the same hotel scores than the scale on TripAdvisor (1-5).

3. Methodology

In this study we analyze the hotels of the top destinations in the world according to the 2015 TripAdvisor Ranking, dividing them into four regions, as propose by Banerjee & Chua, (2016): America (AME), Asia and Pacific (ASP), Europe (EUR), and the Middle East and Africa (MEA). We then split these regions into countries and cities.

In April 2016 we automatically gathered the rankings of the hotels on Booking.com and TripAdvisor: the number of reviews on both websites, the ranking and scoring, hotel name, city and country, and the hotel category (the latter of these variables is the hotel star category according to Booking.com).

The data is collected using an automatically controlled web browser (developed in Python) that simulates a user navigation (clicks and selections) for TripAdvisor and Booking.com. Once the data is available, a new data set is created by joining corresponding data for a given hotel from both websites. The joint criteria are used for every city if:

- the hotel name is exactly the same.

- the hotel name from one site is contained, entirely, in the name from the other site (the choosing of container and contained depending on name length, container chosen as the longest name available); and
- no match is found, then the Ratcliff/Obershelp similarity (Ratcliff & Metzener, 1988) is computed between each possible pair of names (one from Booking.com and one from TripAdvisor).

The list of distances is then sorted, and the greatest (best match) chosen. If that similarity is higher than 0.85 (that is, 85% of the letters match considering position), the pair is chosen, and the names removed from both lists.

On Booking.com, we filter the results by “Property type”, selecting the “Hotels” and “Review score” rated by “All reviewers” option. Once gathered, all of the hotels in each city are compared with TripAdvisor. On TripAdvisor, we only take into account “Hotels”, discarding other options and sorting them by “Ranking”. Having obtained the two lists (69,997 hotels on TripAdvisor and 40,580 on Booking.com), we automatically compared the hotels listed on both websites. The result is 20,880 hotels that matched both websites. The missing values are eliminated from all variables and the final result is 19,660 hotels, as shown in Table 1.

There are 11,871,134 reviews on Booking.com and 8,812,826 on TripAdvisor. To calculate the score (and therefore the position in the ranking), Booking.com does not take into account hotels with fewer than 5 reviews, so the minimum number of reviews on this website is 5, whereas on TripAdvisor it is 1, as shown in Table 1. The review mean is higher on Booking.com than on TripAdvisor.

The data collection from each destination is conducted simultaneously from both sites in order to have minimum variation. Since both websites are active and the data is modified over time, the data is extracted in less than 48 hours.

Table 1. Sample selection

	TripAdvisor	Booking.com
Countries	68	67
Destinations	451	447
Hotels	69,997	40,580
Hotels on both websites	19,660	19,660
Total reviews	8,812,826	11,871,134
Min. Review	1	5
Max. Review	16,750	18,120

Source: Compiled by the authors based on data from Booking.com and TripAdvisor

The statistical calculations are performed using R version 3.2.1 software.

To check the first hypothesis, $H1$, we defined a linear model for the ranking position on TripAdvisor (Ar) versus the ranking position on Booking (Br), as

$\mathrm{Ar} = \mathrm{Br} \cdot \beta + \epsilon$ (Eq. 1)

In order to check $H1$, it is necessary to estimate whether or not the linear regression model allows the ranking position to be inferred and if it is statistically significant. In other words, the null hypothesis and alternative hypothesis could be stated as follows:

$$H1_0 : \beta = 0$$

$$H1_1 : \beta \neq 0$$

Under the null hypothesis, the following test statistic (Faraway, 2014):

$$F = \frac{\frac{(tss-rss)}{(p-1)}}{\frac{rss}{(n-p)}} \text{ (Eq. 2)}$$

follows a Fisher distribution, where n = (the number of variables), p = 19,660 (number of samples), rss = $\sum_{i=1}^{n}(Ar_i - Br_i \cdot \beta)$ and $tss = \sum_{i=1}^{n}(ar_i - \overline{ar})$.. Here we denote ar_i and br_i as the sample values of Ar and Br, respectively, and $\overline{ar}$ as the mean value of Ar.

Additionally, we also show the Spearman ranking correlation coefficient:

$$r_s = \frac{\sum_{i=1}^{n}(br_i - \overline{br})(ar_i - \overline{ar})}{\sqrt{\sum_{i=1}^{n}(br_i - \overline{br})^2 \sum_{i=1}^{n}(ar_i - \overline{ar})^2}}$$

in order to determine the strength of the correlation. Missing values are eliminated from both variables to obtain identical pairs.

In relation to hypothesis $H2$, we denote As and Bs as the standardized values of scores for each hotel. As the data sets for TripAdvisor and Booking.com have different rating scales, from 1 to 5 for TripAdvisor and from 2.5 to 10 for Booking.com, both data sets are standardized to a scale from 0 to 1. Furthermore, samples are paired by score for the same hotel on both websites. Thus, $H2$ null and alternative hypotheses could be stated as follows:

$$H2_0 : \overline{as} - \overline{bs} = 0$$

$$H2_1 : \overline{as} - \overline{bs} \neq 0$$

where $\overline{as}$ and $\overline{bs}$ are the mean values of As and Bs, respectively. In this case, the test statistic is:

$$t = \frac{\overline{as} - \overline{bs}}{\sqrt{\frac{\sum_{i=1}^{n}((as_i - as)(bs_i - \overline{bs}))^2}{n(n-1)}}}$$

following a Student's-t distribution with $n - 1$ degrees of freedom (df).

As we work with a large volume of data and apply the central limit theorem, the population of sample means is assumed to be normal.

4. Results

For H1 with the hotels that match on both websites, the Spearman correlation coefficient is $r_S = .87$ and the p-value for the test statistic (Eq. 2) is p < .001. Thus, evidence is found to support the relationship between the two rankings. Table 2 shows the results after analyzing the data by region (AME, ASP, EUR, and MEA), sub region (Africa, Asia, Caribbean, Central America, Europe, Middle East, North America, South America, and South Pacific), and city.

Table 2. Spearman correlation coefficient for Booking.com and TripAdvisor rankings by subregions and cities

Subregion/City	n	r_S	β	F
AME	4130	.85**	.83**	1.46**
ASP	5922	.83**	.21**	2,513.00**
EUR	8809	.90**	.86**	36,710.00**
MEA	799	.83**	.45**	1,968.00**
Africa	289	.76**	.16**	157.60**
Asia	5573	.82**	.20**	2,256.00**
Caribbean	68	.67**	.23**	20.37**
Central America	167	.80**	.81**	455.10**
Europe	8809	.90**	.86**	36710**
Middle East	510	.90**	.55**	3,940.00**
North America	2254	.83**	.79**	6,401.00**
South America	1641	.88**	.88**	7,998.00**
South Pacific	349	.79**	.74**	627.10**
Paris	855	.85**	.75**	2,324.00**
Istanbul	607	.70**	.94**	571.80**
Rome	524	.86**	.63**	1,319.00**
London	485	.90**	.66**	1,935.00**
Bangkok	337	.86**	.76**	883.60**
Tokyo	331	.73**	.51**	369.00**
Shanghai	290	.76**	.11**	127.20**
Berlin	285	.81**	.67**	458.20**
Montreal	66	.96**	.72**	620.80**
Dublin	74	.95**	.63**	610.90**
Hamburg	155	.30**	.23**	11.88**

Note. Coefficients are shown in the table; $^{**}p < .001$

As shown in Table 2, by sub region, the strongest correlations are in Europe and the Middle East, and the weakest are in the Caribbean because there are only 68 hotels spread across 9 countries.

Moreover, the analysis by city with the highest number of hotels (Paris, Istanbul, Rome, London, Bangkok, and Tokyo) shows that, apart from Istanbul, they have a strong Spearman correlation coefficient.

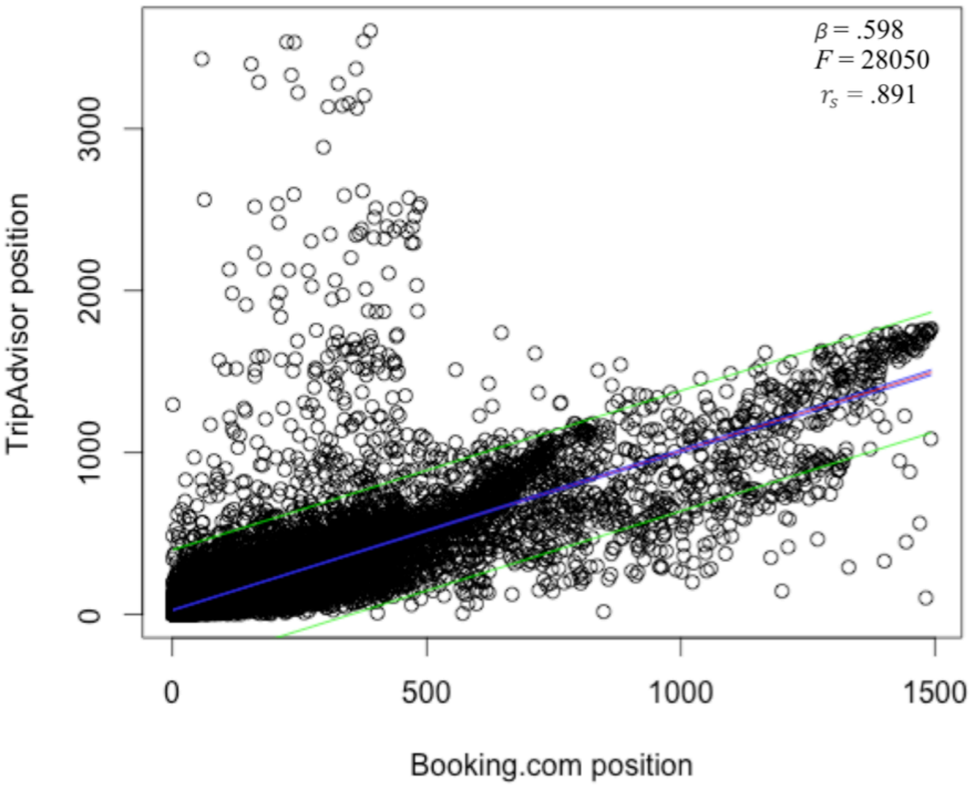
In general, and except for certain cities with few hotels, the results show a direct positive relationship between rankings. Thus, there is some relationship between the Booking.com and TripAdvisor rankings, since, in most cases, a strong statistically significant correlation is obtained, indicating that the position in the two rankings is similar.

As with the previous tests, the regressions are statistically significant $p < .001$ in all regions (AME, ASP, EUR, and MEA), so evidence is found to support the idea that there is a relationship between the rankings of TripAdvisor and Booking.com.

With all dataset, regression analyses establish a statistically significant relationship between the two variables ($F = 28050$; $\beta = .60$, $p < .001$). Thus, as the TripAdvisor position increases, the Booking.com position is likely to increase, and vice versa. Therefore, there is a statistically significant relationship between both rankings, as can be seen in Table 2.

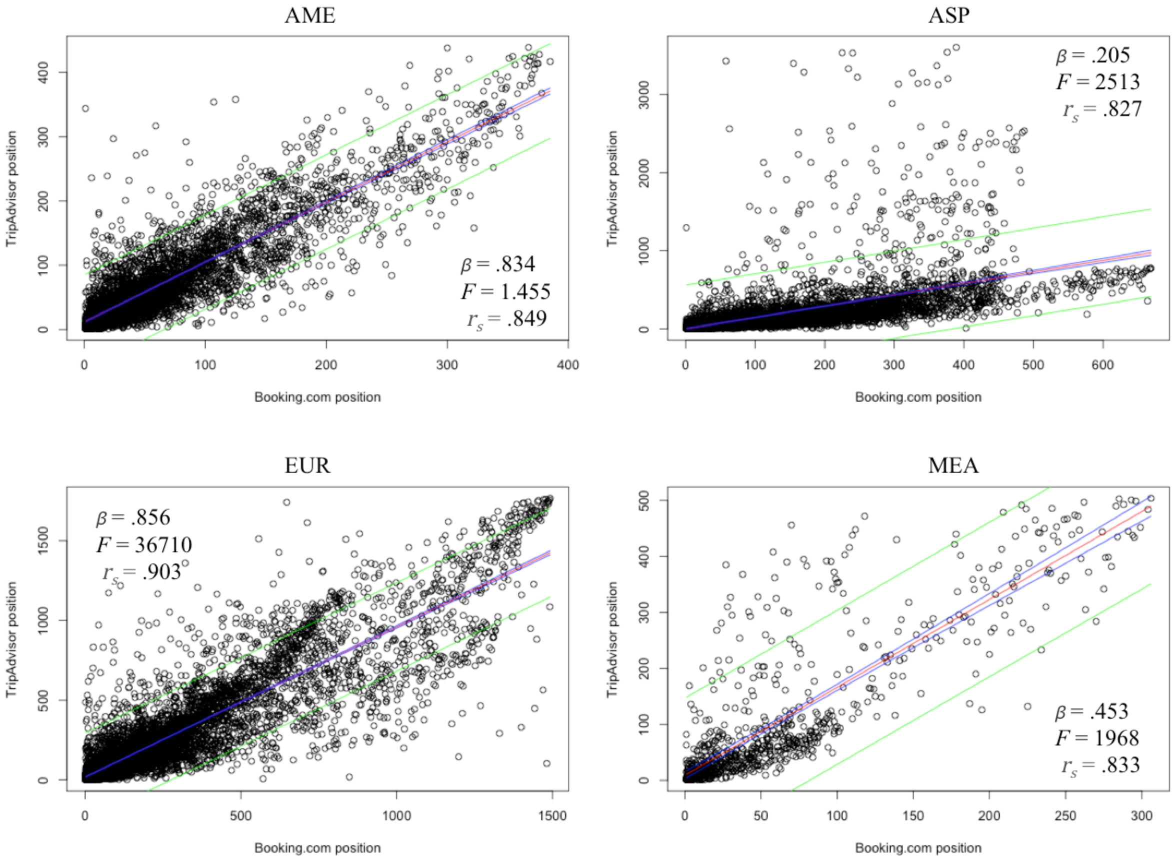
Figure 2 and Figure 3 plot the fitted model represented in Eq. 1. The gray lines plot the confidence interval for the mean observed values, the doted lines define the confidence interval for predicted observations, and the black line plots the fitted model. In Figure 2 all of the aggregate data is plotted, while in Figure 3 plots refer to regions.

Figure 2. Linear model between TripAdvisor and Booking.com rankings



Source: Compiled by the authors based on data from Booking.com and TripAdvisor

Figure 3. Linear model between TripAdvisor and Booking.com ranking by regions



Source: Compiled by the authors based on data from Booking.com and TripAdvisor

As explained, Booking.com uses a scale from 2.5 to 10 and TripAdvisor from 1 to 5. With these scales, the minimum ratings for the hotels is 3 on Booking.com and 1 on TripAdvisor, meaning that among more than 20,000 hotels the minimum on Booking.com is never reached. However, the maximum ceiling of the scales (10 and 5, respectively) is reached in both cases. Booking.com calculates the global score with a mean of 6 items (value, services, comfort, clean, staff, and location). On TripAdvisor, the user gives a direct score and, later on, can assess other sections individually. However, these are not taken into account in the final score.

From among the items rated by users, the one with the highest mean is staff, followed by location and comfort, as shown in Table 3.

Table 3. Descriptive statistics of the Booking.com score

Booking.com	Total score	Value	Services	Comfort	Clean	Staff	Location	Wi-Fi
N	19,660	19,660	19,660	19,660	19,660	19,660	19,660	17,068
Min	3.7	2.8	3.0	3.2	2.8	3.6	3.3	2.5
Max	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
Mean	7.95	7.60	7.60	7.79	8.13	8.24	8.30	7.61
SD	0.87	0.82	1.03	1.06	1.04	0.88	0.93	1.21

Source: Compiled by the authors based on data from Booking.com

The countries with the lowest scoring hotels on TripAdvisor are in Malaysia, the Dominican Republic, Singapore, Denmark, and Indonesia; on Booking.com they are in Egypt, China, India, the Dominican Republic, and Malaysia. The highest rated hotels on TripAdvisor are in Bermuda, Fiji, Anguilla, and Nicaragua; on Booking.com they are in Bermuda, Fiji, Guatemala, and Honduras.

Bearing in mind the scoring scale and rating method of each website, it is possible to observe that most reviews are in the upper half of the scale, so both systems are systematically positively biased all over the world. Thus, on TripAdvisor, 95.68% of the hotels are rated at 3 or more (midpoint on the scale), whereas on Booking.com, 95.57% of the hotels are rated above 6.25 (midpoint on the scale). On TripAdvisor, the results are similar in all regions, but on Booking.com we can see that in MEA and ASP the percentage above the mean is lower than in AME and EUR.

At the top of the scale, we find that 3.47% of the hotels on TripAdvisor obtain the maximum score, while only 1.29% of the hotels on Booking.com do the same. On average, the hotels that achieve the highest score are those in AME on TripAdvisor (3.93), as well as on Booking.com (8.11), and the hotels with the highest dispersion are those in MEA (0.67).

Table 4. Ratings of hotels on TripAdvisor

Region	**Hotels**	**Mean score**	**SD score**	**Excellent (5) %**	**Very good (4.5-4) %**	**Average (3.5-3) %**	**Poor (2.5-2) %**	**Terrible (1.5-1) %**
AME	4,130	3.93	0.57	2.95	65.11	28.74	3.00	0.19
ASP	5,922	3.84	0.58	3.16	56.70	36.14	3.77	0.24
EUR	8,809	3.90	0.62	3.85	62.52	28.70	4.59	0.35
MEA	799	3.91	0.67	4.38	61.70	28.29	5.51	0.13
Total	19,660	3.89	0.60	3.47	61.28	30.93	4.04	0.27

Source: Compiled by the authors based on data from TripAdvisor

Table 5. Ratings of hotels on Booking.com

Region	Hotels	Mean score	SD score	Excep-tional (10-9.5) %	Superb (9.4-9) %	Fabulo us (8.9-8.6) %	Very good (8.5-8) %	Good (7.9-7)	Pleasant (6.9-6)	Review score <6
AME	4,130	8.11	0.79	1.33	10.53	19.30	32.11	28.62	6.59	1.53
ASP	5,922	7.67	0.96	0.88	6.30	10.74	24.54	35.58	17.44	4.53
EUR	8,809	8.07	0.79	1.52	10.23	16.35	33.43	29.87	7.07	1.53
MEA	799	7.73	1.00	1.63	7.88	12.39	25.41	32.04	15.14	5.51
Total	19,660	7.95	0.87	1.29	9.01	15.12	30.15	31.41	10.42	2.59

Source: Compiled by the authors based on data from Booking.com

Table 6. Ratings of hotels

Region	**Above 6.25 Booking.com (%)**	**Below 6.25 Booking.com (%)**	**3 or above TripAdvisor (%)**	**Below 3 TripAdvisor (%)**
AME	97.38	2.62	96.80	3.20
ASP	92.20	7.80	96.00	4.00
EUR	97.41	2.59	95.06	4.94
MEA	90.86	9.14	94.37	5.63
Total	95.57	4.43	95.68	4.32

Source: Compiled by the authors based on data from Booking.com and TripAdvisor

To check *H2* with the standardized scale (0-1) for both websites, a Student's t-test is done with pairs of variables, as the hotels analyzed are the same in the two different rankings.

The results allow us to reject the null hypothesis that the score means are equal on both websites, so we confirm that on TripAdvisor the score mean is lower than on Booking.com (t = -4.86, df = 19,659, p < .001). However, the effect size is negligible (Cohen's d = .03) with all dataset, so an in-depth analysis split by regions and by hotel category is carried out. Table 7 shows the Student's t-test by region and by hotel category in which the rating scale mean is higher for 5-star hotels worldwide on TripAdvisor, is statistically significant, and has the largest effect size of all dataset, especially, the ones from MEA.

On Booking.com, the scoring scale benefits 1 to 3-star hotels in AME and EUR with a low-medium effect size, and is detrimental to 4-star hotels in ASP and in MEA with a low effect size. For all other hotels, the null hypothesis is accepted, as the mean differences are equal and/or the effect size is negligible.

Table 7. Student's t-test and effect size (Cohen's d)

Region/ Hotel category (stars)	1		2		3		4		5	
	t	*d*	*t*	*d*	*t*	*d*	*t*	*d*	*t*	*d*
AME	-2.52*	.41	-9.63**	.47	-1.56**	.26	-3.39**	.09	6.31**	.32
ASP	1.71	.17	5.05**	.18	4.13**	.08	9.32**	.23	15.39**	.53
EUR	-6.18**	.44	-13.54**	.44	-16.27**	.29	-7.70**	.14	9.91**	.39
MEA	0.42	.12	-0.45	.07	-0.34	.03	5.73**	.39	9.67**	.69

Note. Coefficients are shown in the table; $^{*}p < .05$ $^{**}p < .001$

5. Discussion

For most of the cities analyzed, the results show that there is a high degree of relationship between both websites' rankings, indicating very strong statistically significant correlations. They likewise show that the possible publication of fake reviews on TripAdvisor do not seem to be prevalent, as both rankings behave similarly. Hence, having analyzed the data, it can be said that the verification systems of both websites do not affect the position of hotels.

The rankings of both websites are checked and the fact that they present such a high statistically significant correlation is important given their usefulness for comparing different options, thereby reducing the time and effort needed to identify the most suitable accommodation (Filieri & McLeay, 2013).

With regard to the second hypothesis, the unique rating scale of Booking.com (from 2.5 to 10) compared to TripAdvisor's scale (from 1 to 5) benefits 1 to 3-star hotels in AME and EUR and is detrimental to 5-star hotels worldwide, and 4-star hotels in ASP and MEA. The reason why 5-star hotels have higher scores on TripAdvisor than on Booking.com could be that the score is assigned directly, whereas on Booking.com the scoring system is the arithmetic average of 6 elements as shown in Figure 1 (comfort, value, clean, staff, location and services). Thus, it is necessary for all users rating a hotel to give the maximum score to all items, as suggested by Mellinas et al., (2016) in their research comparing hotels on Booking.com and Priceline which seems more difficult than getting the maximum score for a single item.

Another reason why hotels with high standards of quality get worse scores on Booking.com than on TripAdvisor could be in how reviews are posted. On TripAdvisor users post a general review when they decide to enter on the platform, but on Booking.com users receive an email asking to rate the experience and to post a review explaining both the pros and cons separately, which obliges users to also think of the negative attributes that might be overlooked when answering in a free format.

The results show that the item with the highest mean is staff, followed by location. Cleanliness, a critical item in customer ratings (Barreda & Bilgihan, 2013) is in third place. Value for money, which generally captures all items to determine the overall score (Fuchs & Zanker, 2012), is the second most underrated item in this study. The highest average of all items is location. An explanation for this fact might be that the traveler already knows where a hotel is located and, therefore, it is the item that generates less uncertainty on the trip and less surprise in the experience. It is worth noting that the geographical location of a hotel has the highest average of all items, essentially because it cannot be changed or improved by the staff once the property is built (Xie et al., 2014). Of the 20,000 hotels, none had a score below 3.3 for location, and none below 3.6 for staff.

With the overall rating of hotels on Booking.com, no hotel had a score less than 3.7; it did not happen on TripAdvisor, where some hotels had the minimum score. Only 4.43% of the hotels had a score below 6.25 on Booking.com, which, on a scale from 2.5 to 10, is in the middle. Since the users of this system are unaware of this fact, it may favor their perception that most hotels on Booking.com are above 5, a score that is in the middle of a typical scale from 0 to 10, Mellinas et al., (2015: 74) point out that, "this scoring system does not appear to be illegal but could indicate a lack of honesty with customers."

TripAdvisor achieves a score below 3 (midpoint on a scale from 1 to 5) in 4.32% of the cases, so it seems that the number of hotels rated poorly on both websites is similar. Although Bjørkelund et al. (2012: 235) note that scores from both sources shift toward the higher end of the scale, Booking.com scores are noticeably higher, with more than 80% of review scores higher than 6 on a scale from 0-10. Bjørkelund et al. (2012) do not detect that the scale is from 2.5 to 10 and other studies conclude that there is a positive bias on Booking.com when compared to TripAdvisor. This bias could be due to the fact that TripAdvisor offers "a valuation related more to 'real' quality (services offered) than to just administrative category or price" (Fernández-Barcala et al., 2010, p. 358). However, the results show a positive bias on both Booking.com and TripAdvisor, and the review scores on both websites are found to be greatly skewed from the middle to the top of the scale, in line with a study conducted on FlipKey.com reviews (Racherla, Connolly, & Christodoulidou, 2013).

6. Conclusions

Fraudulent practices on TripAdvisor cannot be confirmed in this study even though cases are documented in other studies (Mayzlin et al., 2012; Mellinas Cánovas, 2015; Mkono, 2015) because it can be concluded that the verification system on TripAdvisor does not affect the position of hotels when compared with Booking.com because of the strong statistically significant correlation between both rankings for most of the cities.

Thanks to this relationship, hotel managers can roughly know which position their hotels will have on Booking.com based on the position obtained on TripAdvisor, as well as if the scoring scale on Booking.com benefits or harms them. This fact could be an interesting information to have before deciding whether or not to work with this online hotel-booking website, as online visibility is important for profitability (Neirotti et al., 2016).

The main contribution of this study is that suspicions of fraud on TripAdvisor because of its unverified user reviews are not the norm on this platform compared with Booking.com, perhaps because the reputation management system on TripAdvisor increases the motivation of users to contribute reliable reviews (Yoo, Sigala, & Gretzel,, 2016). As the number of reviews grows, the impact of possible fake reviews falls, as they are overwhelmed by genuine consumer-generated content, thanks to the tendency of human behavior to embrace “the power of the crowd”. Moreover, as stated by O’Connor, (2008) TripAdvisor appears to be doing a good job of policing its system.

The distinctive feature of this research is comparing ranking and not scores, since product ranking is now “the strongest antecedent of high-involvement travelers’ adoption of information from online reviews, which is a new finding in eWOM research” (Filieri & McLeay, 2013: 52). Moreover, it is important to note that this study extends the number of investigations analyzing a very large sample of hotels in more than 400 cities. As (Xiang, Schwartz, Gerdes, & Uysal, 2015) point out there are very few studies in this field that explore the capacity of big data.

A lack of veracity is associated with TripAdvisor in some studies (Gerrard, 2012; Morrison, 2012; Palmer, 2013; Rawlinson, 2011; Smith, 2012), whereas Booking.com creates an image of greater information reliability because its reviews are subject to a verification system. Some authors assert that the average differences between the two websites could be due to it being harder to include false negative reviews on Booking.com (Estárico, Medina, & Marrero, 2012). The greater credibility of Booking.com is discussed not only in academic studies but also in studies by online reputation companies such as KwikChex (Gutiérrez Taño, Parra López, & González Wetherill, 2014).

When the Booking.com scoring system is analyzed in depth, the fact that it may lack a degree of honesty with unsuspecting customers (Mellinas et al., 2015) is found to benefit some hotels and be detrimental to others, especially 5-star hotels worldwide. As hoteliers become aware that the scoring system on Booking.com benefits some hotels, they should take it into account when deciding which online travel agency is best to sell their property. Meanwhile, users should be aware of the rating scale on Booking.com in order to not have unpleasant surprises, thinking that a hotel with a score of 5 is just in the middle. In reality, on Booking.com a score of 6.25 is necessary to be in the middle.

The validity of both websites is demonstrated, regardless of whether the reviews are by 'real users' on Booking.com or otherwise on TripAdvisor. Both platforms are valid as a travel information source, as well as for researchers, despite unverified users posting their opinions. However, researchers should take the real rating scales into account.

Knowing the behavior of the verified and unverified reviewers is important, not only for hotels or restaurants but also for the eWOM of tourist attractions, for which it is much more complicated to create a system for validating whether or not reviewers have really visited the attractions, but also for the recent service launched by TripAdvisor that allows passengers to review their flight experiences (TripAdvisor, 2016b). It is also important on a research level and is a field yet to be explored.

Therefore, given the importance acquired by TripAdvisor among the worldwide community of travelers, the hotel industry should take advantage of this platform's potentialities and not refute it because of its verification system. Encouraging users to comment in order to obtain a large number of reviews would be optimal to ensure that opinions more accurately reflect the reality of each hotel. Customer opinions are also a source of segmentation that allows the better positioning of each hotel (Martin-Fuentes, Fernandez, & Mateu, 2016). It is not beneficial to cheat users with fictitious reviews about the hotel because future guests will be disappointed if the hotel does not meet their expectations.

This study shows that when opinions are given on different websites with different rating and user verification systems, the outcome in terms of ranking ultimately tends to be the same, although there are differences in how to collect the reviews. Booking.com sends an email asking for a review within the following 28 days after the stay; and TripAdvisor users can opine whenever they want. The rankings are similar on each site also despite the differences in the scoring scales and in the survey methods (free format or pros and cons separately), and the antiquity of the ratings (TripAdvisor calculates the ratings based on all reviews received while Booking.com does not take into account the reviews that are more than 24 months old). Our research is a grounded work that allows us and other researchers to deepen the subject on suspicious unverified users on TripAdvisor and on the measuring scales in sales and advice platforms.

Although hotels all over the world are analyzed in this study, using data from Booking.com and TripAdvisor, these websites can produce a cultural bias because they are used by some nationalities more than others. Empirical replications using other channels (e.g., Ctrip) to find if there are behavioral differences by nationality may provide more insight to this discussion.

Acknowledgements

This work was partially funded by the Spanish Ministry of the Economy and Competitiveness: research project TIN2015-71799-C2-2-P and ENE2015-64117-C5-1-R.

This research article has received a grant for its linguistic revision from the Language Institute of the University of Lleida (2016 call).

7. References

Anderson, C. K. (2012). The Impact of Social Media on Lodging Performance. *Cornell Hospitality Report*, *12*(15), 6-11.

Anderson, E. W. (1998). Customer Satisfaction and Word of Mouth. *Journal of Service Research*, *1*(1), 5–17.

Arndt, J. (1967). Role of product-related conversations in the diffusion of a new product. *Journal of Marketing Research*, *4*(3), 291–295.

Ayeh, J. K., Au, N., & Law, R. (2013). "Do We Believe in TripAdvisor?" Examining Credibility Perceptions and Online Travelers' Attitude toward Using User-Generated Content. *Journal of Travel Research*, *52*, 437–452.

Balagué, C., Martin-Fuentes, E., & Gómez, M. J. (2016). Fiabilidad de las críticas hoteleras autenticadas y no autenticadas: El caso de TripAdvisor y Booking.com. *Cuadernos de Turismo*, *38*.

Banerjee, S., & Chua, A. Y. K. (2016). In search of patterns among travellers' hotel ratings in TripAdvisor. *Tourism Management*, *53*, 125–131.

Barreda, A., & Bilgihan, A. (2013). An analysis of user-generated content for hotel experiences. *Journal of Hospitality and Tourism Technology*, *4*(3), 263–280.

Bjørkelund, E., Burnett, T. H., & Nørvåg, K. (2012). A study of opinion mining and visualization of hotel reviews. In *Proceedings of the 14th International Conference on Information Integration and Web-based Applications & Services - IIWAS '12* (p. 229). New York, USA: ACM Press.

Booking.com. (2016). About Booking.com. Retrieved September 23, 2016, from http://www.booking.com/content/about.en-gb.html

Burton, J., & Khammash, M. (2010). Why do people read reviews posted on consumer-opinion portals? *Journal of Marketing Management*, *26*(3–4), 230–255.

Cantallops, A. S., & Salvi, F. (2014). New consumer behavior: A review of research on eWOM and hotels. *International Journal of Hospitality Management*, *36*, 41–51.

Casaló, L. V., Flavián, C., Guinalíu, M., & Ekinci, Y. (2015). Do online hotel rating schemes influence booking behaviors? *International Journal of Hospitality Management*, *49*, 28–36.

Chaves, M. S., Gomes, R., & Pedron, C. (2012). Analysing reviews in the Web 2.0: Small and medium hotels in Portugal. *Tourism Management*, *33*(5), 1286–1287.

Cheung, C. M. K., & Thadani, D. R. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. *Decision Support Systems*, *54*(1), 461–470.

Chevalier, J. A., & Mayzlin, D. (2006). The Effect of Word of Mouth on Sales : Online Book Reviews, *43*(3), 345–354.

Chitika. (2013). The Value of Google Result Positioning. Retrieved August 6, 2015, from https://chitika.com/google-positioning-value

Dellarocas, C. (2003). The digitization of word of mouth: Promise and challenges of online feedback mechanisms. *Management Science*, *49*(10), 1407–1424.

Duan, W., Gu, B., & Whinston, A. B. (2008). The dynamics of online word-of-mouth and product sales—An empirical investigation of the movie industry. *Journal of Retailing*, *84*(2), 233–242.

Estárico, E. H., Medina, L. F., & Marrero, S. M. (2012). Una aproximación a la reputación en línea de los establecimientos hoteleros españoles. *Papers de Turisme*, (52), 63–88.

Faraway, J. J. (2014). *Linear models with R*. CRC Press.

Fernández-Barcala, M., González-Díaz, M., & Prieto-Rodríguez, J. (2010). Hotel quality appraisal on the Internet: a market for lemons? *Tourism Economics*, *16*(2), 345–360.

Filieri, R., & McLeay, F. (2013). E-WOM and Accommodation: An Analysis of the Factors That Influence Travelers' Adoption of Information from Online Reviews. *Journal of Travel Research*, *53*(1), 44–57.

Fuchs, M., & Zanker, M. (2012). Multi-criteria Ratings for Recommender Systems: An Empirical Analysis in the Tourism Domain, In *E-Commerce and Web Technologies: 13th International Conference, EC-Web 2012, Vienna, Austria, September 4-5, 2012. Proceedings*, 100–111.

Gerrard, N. (2012). Battle with TripAdvisor won but the war goes on. *Caterer & Hotelkeeper*, *202*, 5. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=hjh&AN=72953162&lang=es&site=ehost-live&scope=site

Ghose, A., Ipeirotis, P. G., & Li, B. (2012). Designing ranking systems for hotels on travel search engines by mining user-generated and crowdsourced content. *Marketing Science*, *31*(3), 493–520.

Gretzel, U., & Yoo, K. H. (2008). Use and Impact of Online Travel Reviews. In P. O'Connor, W. Höpken, & U. Gretzel (Eds.), *Information and Communication Technologies in Tourism* (pp. 35–46). Vienna: Springer Vienna.

Grindlinger, G. S. (2012). Federal court dismisses defamation claims against TripAdvisor. *Hospitality Law*, *27*, 1–4. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=hjh&AN=83716061&lang=es&site=ehost-live&scope=site

Gutiérrez Taño, D., Parra López, E., & González Wetherill, Y. C. (2014). La influencia de la autentificación de identidad en las valoraciones online de los hoteles. In *XVIII Congreso Nacional Asociación Española de Experto Cientificos en Turismo*. Benidorm.

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? *Journal of Interactive Marketing*, *18*(1), 38–52.

Jin, G. Z., & Whalley, A. (2007). The Power of Information: How Do US News Rankings Affect the Financial Resources of Public Colleges?

Leung, D., Law, R., van Hoof, H., & Buhalis, D. (2013). Social Media in Tourism and Hospitality: A Literature Review. *Journal of Travel and Tourism Marketing*, *30*(1–2), 3–22.

Litvin, S. W., Goldsmith, R. E., & Pan, B. (2008). Electronic word-of-mouth in hospitality and tourism management. *Tourism Management*, *29*(3), 458–468.

Liu, B., Pennington-Gray, L., Donohoe, H., & Omodior, O. (2015). New York City Bed Bug Crisis as Framed by Tourists on Tripadvisor. *Tourism Analysis*, *20*(2), 243–

250.

Martin-Fuentes, E. (2016). Are guests of the same opinion as the hotel star-rate classification system? *Journal of Hospitality and Tourism Management*, *29*, 126–134.

Martin-Fuentes, E., Fernandez, C., & Mateu, C. (2016). Las estrellas muestran el camino: coincidencia entre satisfacción y categoría hotelera. In Universidad de Malaga (Ed.), *ICT & Tourism International Conference TURITEC*. Malaga.

Mayzlin, D., Dover, Y., & Chevalier, J. A. (2012). *Promotional reviews: An empirical investigation of online review manipulation* (RPRT). National Bureau of Economic Research.

Melian-Gonzalez, S., Bulchand-Gidumal, J., & Gonzalez Lopez-Valcarcel, B. (2013). Online Customer Reviews of Hotels: As Participation Increases, Better Evaluation Is Obtained. *Cornell Hospitality Quarterly*, *54*(3), 274–283.

Mellinas, J. P., Martínez María-Dolores, S.-M., & Bernal García, J. J. (2015). Booking.com: The unexpected scoring system. *Tourism Management*, *49*, 72–74.

Mellinas, J. P., Martínez María-Dolores, S.-M., & Bernal García, J. J. (2016). Effects of the Booking.com scoring system. *Tourism Management*, *57*, 80-83 .

Mellinas Cánovas, J. P. (2015). *Análisis y aplicaciones de los sistemas de medición de la reputación online de los hoteles*. Universidad Politécnica de Cartagena.

Mkono, M. (2015). “Troll alert!”: Provocation and harassment in tourism and hospitality social media. *Current Issues in Tourism*, 1–14.

Morosan, C. (2013). The Impact of the Destination’s Online Initiatives on Word of Mouth. *Tourism Analysis*, *18*(4), 415–428.

Morrison, S. (2012). TripAdvisor Under Fire for “Real Traveller” Contribution Claim.

Retrieved December 10, 2015, from http://www.guardian.co.uk/media/2012/feb/01/tripadvisor-criticise-honest-contribution-claim

Neirotti, P., Raguseo, E., & Paolucci, E. (2016). Are customers' reviews creating value in the hospitality industry? Exploring the moderating effects of market positioning. *International Journal of Information Management*, *36*(6), 1133–1143.

O'Connor, P. (2008). User-Generated Content and Travel : A Case Study on Tripadvisor.Com. *Business*, *21*, 47–58.

Palmer, M. (2013). It's the hotel review website that millions use to help choose their holiday. But… Can you trust a single word on TripAdvisor? Retrieved September 11, 2014, from http://www.dailymail.co.uk/news/article-2384519/Its-hotel-review-website-millions-use-help-choose-holiday-But--Can-trust-single-word-Trip-Advisor.html

Pavlou, P. A., & Dimoka, A. (2006). The nature and role of feedback text comments in online marketplaces: Implications for trust building, price premiums, and seller differentiation. *Information Systems Research*, *17*(4), 392–414.

Pope, D. G. (2009). Reacting to rankings: evidence from "America's Best Hospitals". *Journal of Health Economics*, *28*(6), 1154–65.

Racherla, P., Connolly, D. J., & Christodoulidou, N. (2013). What Determines Consumers' Ratings of Service Providers? An Exploratory Study of Online Traveler Reviews. *Journal of Hospitality Marketing & Management*, *22*(2), 135–161.

Ratcliff, J. W., & Metzener, D. E. (1988). Pattern-matching-the gestalt approach. *Dr Dobbs Journal*, *13*(7), 46.

Rawlinson, K. (2011). Hotelier's business collapses after "good" reviews on website. Retrieved from http://www.independent.co.uk/travel/news-and-advice/hoteliers-business-collapses-after-good-reviews-on-website-2363191.html

Schuckert, M., Liu, X., & Law, R. (2015). Hospitality and Tourism Online Reviews: Recent Trends and Future Directions. *Journal of Travel & Tourism Marketing*, *32*(5), 608–621.

Smith, O. (2012). TripAdvisor under fire over fraud detection. Retrieved September 3, 2014, from http://www.telegraph.co.uk/travel/travelnews/9160472/TripAdvisor-under-fire-over-fraud-detection.html

Solomon, M., Russell-Bennett, R., & Previte, J. (2012). *Consumer behaviour*. Pearson Higher Education AU.

Sorensen, A. T. (2007). Bestseller lists and product variety. *The Journal of Industrial Economics*, *55*(4), 715–738.

Sparks, B. A., & Browning, V. (2011). The impact of online reviews on hotel booking intentions and perception of trust. *Tourism Management*, *32*(6), 1310–1323.

Spink, A., & Jansen, B. J. (2006). *Web search: Public searching of the Web* (Vol. 6).Springer Science & Business Media.

Sun, S., Fong, L. H. N., Law, R., & Luk, C. (2015). An Investigation of Gen-Y's Online Hotel Information Search: The Case of Hong Kong. *Asia Pacific Journal of Tourism Research*, *21*(4), 443-456..

Torres, E. N., Adler, H., & Behnke, C. (2014). Stars, diamonds, and other shiny things: The use of expert and consumer feedback in the hotel industry. *Journal of*

Hospitality and Tourism Management, *21*, 34–43.

TripAdvisor. (2016a). Retrieved August 5, 2016, from https://www.tripadvisor.com/PressCenter-c6-About_Us.html

TripAdvisor. (2016b). TripAdvisor. Retrieved November 8, 2016, from https://www.tripadvisorsupport.com/hc/en-us/articles/215955068

Vermeulen, I. E., & Seegers, D. (2009). Tried and tested: The impact of online hotel reviews on consumer consideration. *Tourism Management*, *30*(1), 123–127.

Viglia, G., Minazzi, R., & Buhalis, D. (2016). The influence of e-word-of-mouth on hotel occupancy rate. *International Journal of Contemporary Hospitality Management*, *28*(9), 2035–2051.

Webb, S. (2014). "Give us free meals or I"ll put a bad review on TripAdvisor': Anger at blackmailers using online ratings website to extort free rooms and dinners from hotels and restaurants. Retrieved December 10, 2015, from http://www.dailymail.co.uk/news/article-2623290/Give-free-meals-Ill-bad-review-TripAdvisor-Anger-blackmailers-using-online-ratings-website-extort-free-rooms-dinners-hotels-restaurants.html

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

Xie, K. L., Zhang, Z., & Zhang, Z. (2014). The business value of online consumer reviews and management response to hotel performance. *International Journal of Hospitality Management*, *43*, 1–12.

Ye, Q., Law, R., Gu, B., & Chen, W. (2011). The influence of user-generated content on traveler behavior: An empirical investigation on the effects of e-word-of-mouth to hotel online bookings. *Computers in Human Behavior*, *27*(2), 634–639.

Yen, C.-L. (Alan), & Tang, C.-H. (Hugo). (2015). Hotel attribute performance, eWOM motivations, and media choice. *International Journal of Hospitality Management*, *46*, 79–88.

Yoo, K.-H., Sigala, M., & Gretzel, U. (2016). Exploring TripAdvisor. In R. Egger, I. Gula, & D. Walcher (Eds.), *Open Tourism: Open Innovation, Crowdsourcing and Co-Creation Challenging the Tourism Industry* (pp. 239–255). inbook, Berlin, Heidelberg: Springer Berlin Heidelberg.

Yoo, K. H., & Gretzel, U. (2010). Antecedents and impacts of trust in travel-related consumer-generated media. *Information Technology & Tourism*, *12*(2), 139–152.

5. The more the merrier? Number of reviews versus score on TripAdvisor and Booking.com

Pages 49 to 77 contain this article:

Martin-Fuentes, E., Mateu, C., & Fernandez, C. (2018). The more the merrier? Number of reviews versus score on TripAdvisor and Booking.com. *International Journal of Hospitality & Tourism Administration.* (Accepted on 27 January 2017. Published online on 29 January 2018). http://doi.org/10.1080/15256480.2018.1429337

Journal Metrics
SCImago Journal Rank (SJR): 0.493
Year 2017 Second Quartile
Area: Business, Management and Accounting. Rank 456 of 1,605
Subject area: Tourism, Leisure and Hospitality Management. Rank 42 of 101

INTERNATIONAL JOURNAL OF HOSPITALITY & TOURISM ADMINISTRATION
https://doi.org/10.1080/15256480.2018.1429337

Routledge
Taylor & Francis Group

Check for updates

The more the merrier? Number of reviews versus score on TripAdvisor and Booking.com

Eva Martin-Fuentes [a], Carles Mateu [b], and Cesar Fernandez [b]

[a]Department of Business Administration, University of Lleida, Lleida, Spain; [b]Inspires, Research Institute, University of Lleida, Lleida, Spain

ABSTRACT

The aim of this research is to confirm whether there is a relationship between the number of reviews and the hotel's score on Booking.com and TripAdvisor and whether the relationship is different depending on the geographical area. Moreover, the study endeavors to confirm whether the number of reviews influences the score on each website.

With the analysis of about 13,899 hotels in 146 cities, our findings suggest that there is some lineal relationship between the amount of reviews and the score on TripAdvisor but not on Booking.com. Moreover, by regions on TripAdvisor hotels from Middle East and Africa and Asia and Pacific have a stronger relationship between reviews and score than those from Europe and America.

ARTICLE HISTORY
Received 5 October 2016
Revised 26 January 2017
Accepted 27 January 2017

KEYWORDS
eWOM; TripAdvisor; Booking.com; score; reviews; UGC

5.1. Introduction

Some authors argue that a large number of reviews may encourage potential consumers to decide to buy a product that many other people have also bought (Dellarocas et al., 2007; Godes & Mayzlin, 2004; Park, Lee, & Han, 2007) as it may be seen as a sign of popularity (Zhang, Zhang, Wang, Law, & Li, 2013; Zhu & Zhang, 2010).

Viglia, Furlan, and Ladrón-de-Guevara (2014) concluded that a good or bad review is not the only relevant factor; it is also the number of reviews, giving credibility to the theory that volume counts more than valence (Y. Liu, 2006).

Moreover, a study of 16,000 European hotels on TripAdvisor concluded that as the number of a hotel's reviews increases, the ratings in the reviews become more positive (Melian-Gonzalez et al., 2013).

The aim of this study is to establish whether there is a relationship between the number of reviews and a hotel's score. This aim endeavors to fill a research gap pointed out by Melian-Gonzalez et al. (2013) by comparing hotel reviews on different websites (TripAdvisor and Booking.com) and identifying whether there are any differences depending on the website chosen and on the geographical area. The research question stated if the number of online travel reviews were larger (or smaller), then the better (or worse) the score would be.

5.2. Contribution to the state-of-the-art

The most important finding of this paper is that there is some relationship between the amount of reviews and the score on TripAdvisor, as pointed out by Melian-Gonzalez et al. (2013) in their study conducted on European hotels only. However, in our study, we point out that this trend is not the case worldwide and that scores do not behave in the same way, as the score on TripAdvisor has a stronger relationship with the reviews than it does on Booking.com.

The main conclusion is that there is also a relationship between volume and score on TripAdvisor but not, generally speaking, on Booking.com because any reviews older than 24 months are not taken into account on Booking.com to calculate a hotel's score. When a hotel's score is based on older reviews too, it tends to make the score more positive but does not reflect the current reality thereof. Booking.com deletes old reviews, which allows an overall score to be obtained that is closer to the actual situation.

5.3. Journal paper

The more the merrier? Numbers of reviews versus score on TripAdvisor and Booking.com

Eva Martin-Fuentes*[a], Carles Mateu[b], Cesar Fernandez[b]

University of Lleida

[a] Department of Business Administration

[b] INSPIRES, Research Institute

University of Lleida

E-mail: eva@aegern.udl.cat, carlesm@diei.udl.cat, cesar@diei.udl.cat

*corresponding author

Abstract

The aim of this research is to confirm whether there is a relationship between the number of reviews and the hotel's score on Booking.com and TripAdvisor and whether the relationship is different depending on the geographical area. Moreover, the study endeavors to confirm whether the number of reviews influences the score on each website.

With the analysis of about 13,899 hotels in 146 cities, our findings suggest that there is some lineal relationship between the amount of reviews and the score on TripAdvisor but not on Booking.com. Moreover, by regions on TripAdvisor hotels from Middle East and Africa and Asia and Pacific have a stronger relationship between reviews and score than those from Europe and America.

Keywords: eWOM; TripAdvisor, Booking.com, score, reviews, UGC

1. Introduction

The online users reviews about goods and services have become more important because they influence on other consumers (Boyd *et al.*, 2014) and are an important information source for decision support (Dellarocas *et al.*, 2007). The user control can provide an experience of empowerment and an enriched sense of satisfaction with the outcome of choice (Wathieu *et al.*, 2002).

According to the existing literature, it confirms that there is a positive relationship between the number of reviews (also called volume) and the purchase intention or the increase on sales in different products or services (Dellarocas et al., 2007; Duan *et al.*, 2008; Godes and Mayzlin, 2004; Liu, 2006).

In the hospitality industry, a large number of reviews allows the hotel to have more visibility because they are exposed more frequently; could reflect better the reality of hotel quality, and can lead the idea that more reviews, more guests, so more popular (Xie *et al.*, 2014). Online consumer reviews could be more influential for hotels with a larger volume of reviews because they are more trustworthy (Zhu & Zhang, 2010).

The electronic Word of Mouth (eWOM), has been widely studied in the hospitality industry. Researchers have shown that a larger number of reviews generates effects on bookings (Sparks & Browning, 2011; Vermeulen & Seegers, 2009) and that a positive eWOM generates positive attitudes and increases sales opportunities (Hong, 2006; Karakaya & Barnes, 2010; Lee *et al.*, 2008; Steffes & Burgee, 2013) but, to our knowledge, only few researches have put their attention to know whether the number of reviews influence the rates awarded by past users. In this sense, the research conducted by Melian-Gonzalez *et al.*, (2013: 274) confirmed “the relationship between valence (positive negative or neutral reviews) and volume (the amount of eWOM disseminated), as the number of reviews increases, the valence becomes more balanced, and the negative effect is mitigated".

The aim of this research is to confirm whether there is a relationship between the number of reviews and score on two of the main websites used by the hospitality industry (Booking.com and TripAdvisor) and whether the relationship is different depending on the geographical area and on the website chosen.

Moreover, this study endeavours to confirm whether the number of reviews influences the score on each website.

This introduction is followed by a review of the existing literature on the subject. Then the methodology is presented in section 3, including the information about data collection and the study objectives are set out, the results are put forward in section 4, leading finally to a section for discussion and conclusions of this study.

2. Theoretical background

In what follows, we will introduce on electronic word of mouth (eWOM) and user-generated content (UGC) in the hospitality industry, continuing with the existing studies on the significance of the number of reviews, and finally we will introduce some of the most popular online source of hotel information such as TripAdvisor and Booking.com.

2.1. User-generated content (UGC) and electronic word of mouth (eWOM)

The use of Web 2.0 applications for the sharing of UGC and the creation of new value added services are enormous (Sigala, 2008). The UGC may serve as a new form of word-of-mouth for products and services (Ye et al., 2011).

The word of mouth (WOM) phenomenon has been studied in marketing (Arndt, 1967) and refers to client communications relating to a consumer experience (Anderson, 1998).

The way in which WOM reviews are made, with the advent of Internet, has been extended thanks to consumer-opinion portals (COPs) (Burton & Khammash, 2010), which allow consumers to review products and services, and other people to view these online reviews.

WOM, propagated via Web 2.0, is known as 'electronic word of mouth' (eWOM) (Hennig-Thurau *et al.*, 2004) and according to the most cited definition, eWOM is "all informal communications directed at consumers through Internet-based technology related to the usage or characteristics of particular goods and services, or their sellers" (Litvin *et al.*, 2008: 461).

The importance of personal recommendations to the tourism industry is considerable (Butler, 1980; Cohen, 1972; Morgan *et al.*, 2003) because of the intangible nature of tourism products. In tourism, eWOM has drawn the attention of some researchers from the viewpoint of the independent traveler who uses personal recommendations offered in COPs by other users on sites like TripAdvisor, as the independent traveler seems to rely more and more on them (Jeacle & Carter, 2011; Ye et al., 2011). The online reviews have a dual role, functioning both as informant and as recommender (Park *et al.*, 2007), are an important source of information to travellers (Pan *et al.*, 2007) and "are like narrative stories that enable prospective travelers to relive others' past experience" (Chen & Law, 2016: 364).

EWOM —and the traditional WOM— have been widely analyzed in many studies. They conclude that positive eWOM generates positive attitudes and increases sales opportunities, while negative eWOM generates the opposite effect (Hong, 2006; Karakaya & Barnes, 2010; Lee et al., 2008; Steffes & Burgee, 2013), particularly noticeable in the hospitality sector, as has been shown by numerous studies (Pantelidis, 2010; Susskind, 2002; Vermeulen & Seegers, 2009; Ye *et al.*, 2009). The researches on eWOM in hospitality industry could be grouped into two general lines: the factors related to the generation of comments; and the impacts these comments have on consumers and on company perspective (Cantallops & Salvi, 2014).

Such is the significance of UGC that has forced hoteliers to design organizational strategies of continual vigilance and monitor UGC (Baka, 2016).

A study analyzing business tourists indicated that they read both positive and negative e-comments, but that they make decisions based on positive e-comments (Memarzadeh *et al.*, 2015). Currently, the reviews are potentially effecting traveler decision-making in terms of forming opinions and narrowing choices (Barreda & Bilgihan, 2013).

Consumers' reviews generate more confidence than information from a company itself (Gretzel & Yoo, 2008; Vermeulen & Seegers, 2009), resulting in an increase in the selling prices of rooms for every extra point in the ratings on TripAdvisor (Anderson, 2012).

2.2. Significance of the number of reviews

Some authors argue that a large number of reviews may encourage potential consumers to decide to buy a product that many other people have also bought (Dellarocas et al., 2007; Godes & Mayzlin, 2004; Park et al., 2007) as it may be seen as a sign of popularity (Zhang *et al.*, 2013; Zhu & Zhang, 2010).

Viglia *et al.* (2014) concluded that a good or bad review is not the only relevant factor; it is the number of reviews, giving credibility to the theory that volume counts more than valence (Liu, 2006).

Moreover, a study of 16,000 European hotels on TripAdvisor concluded that as the number of a hotel's reviews increases, the ratings in the reviews are more positive (Melian-Gonzalez et al., 2013).

2.3. TripAdvisor

TripAdvisor is one of the most influential eWOM sources in the hospitality and tourism context (Yen & Tang, 2015). Because of the significance that TripAdvisor has acquired for any accommodation facilities' reputation, it is often the hotel managers' first point of call (Xie et al., 2014).

Numerous studies have been based on data provided by TripAdvisor (Ayeh *et al.*, 2013; Mayzlin *et al.*, 2012; O'Connor, 2008, 2010; Vermeulen & Seegers, 2009; Wilson, 2012). Some point out that the percentage of consumers who consult TripAdvisor before booking a room in a hotel has been increasing (Anderson, 2012), while others suggest that online rating lists are more useful and credible when published by well-known online travel communities like TripAdvisor (Casaló *et al.*, 2015).

In TripAdvisor's own words, it "is the world's largest travel site, reaching 340 million unique monthly visitors, and more than 350 million reviews and opinions". TripAdvisor takes into account to calculate the overall score all the reviews awarded by past users, even the oldest reviews (TripAdvisor, 2016).

2.4. Booking.com

Travel intermediary websites such as Booking.com are a popular online source of hotel information, as are social media websites like TripAdvisor and Facebook (Sun *et al.*, 2015).

Booking.com B.V. is part of the Priceline Group, the world leader in booking accommodation online. Each day, over 1,000,000 room nights are reserved on Booking.com. Established in 1996, Booking.com is available in more than 40 languages, and offers 940,759 active properties in 223 countries and territories (Booking.com, 2016)

After booking a room through Booking.com and staying in the accommodation, the costumer receives an invitation via e-mail to write a comment about the experience. So Booking.com only publishes reviews from users that have booked at least one night in a lodging property through its website and have stayed there. The reviews older than 24 months on Booking.com are not taken into account to calculate the property's overall score, but are shown on this website because "may still be helpful when choosing the perfect place to stay" (Booking.com, 2016).

3. Research aim and methodology

The main goal of this study is to know whether there is a relationship between the number of reviews and the hotel's score, this aim tries to fill a research gap pointed by Melian-Gonzalez et al., (2013) about comparing hotel reviews on different websites. The websites chosen for the research are two of the main in the hospitality industry, TripAdvisor and Booking.com. We would like to know whether, in case there is some relationship between the number of reviews and the score, there are differences depending on the website chosen and on the geographical area, as the research conducted by Melian-Gonzalez et al., (2013) was done only with European hotels.

Moreover, the study endeavors to confirm whether the number of reviews influences the score on each website and according to the literature review, the hypothesis stated is: the larger (or smaller) the number of online travel reviews, the better (or worse) the score is.

In this study, we analyze the hotels of the top destinations in the world according to the TripAdvisor Ranking 2015, dividing them into four regions, as proposed by Banerjee & Chua (2016): America (AME), Asia and Pacific (ASP), Europe (EUR) and Middle East and Africa (MEA). We then split these regions into countries and cities.

In April 2016, we automatically gathered the rankings of the hotels on Booking.com and TripAdvisor: the number of reviews on both websites, the ranking and scoring, hotel name, city and country, and the hotel category (the latter of these variables was the hotel star category according to Booking.com).

The data were collected using a web browser automatically controlled that simulated a user navigation (clicks and selections) for TripAdvisor and Booking.com. Once the data was available, a new data set was created by joining together corresponding data for a given hotel from both websites. The join criteria used was, for every city:

- If hotel name was exactly the same.
- Else if the hotel name from one site was contained, entirely, on the name from the other site (the choosing of container and contained was depending on name length, container chosen as the longest name available).

- If no match was found, then the Ratcliff/Obershelp similarity (Ratcliff & Metzener, 1988) was computed between each possible pair of names (one from Booking.com and one from Tripadvisor),

the list of distances was then sorted, and the greatest one (best match) was chosen, if that similarity was higher than 0.85 (that is 85% of letters match considering position), the pair was chosen, and the names removed from both lists.

The data collection from each destination was conducted the same day from both sites in order to have minimum variation, since both websites are active and the data can be modified over time

On Booking.com, we filtered the property type by selecting "Hotels" and to obtain the ranking we choose the option "Review score", with the rated by "All reviewers". Once gathered, all the hotels in each city were compared with TripAdvisor taken into account only "Hotels" on TripAdvisor sorted them by "Ranking". Having obtained the two lists (69,997 hotels on TripAdvisor and 40,580 on Booking.com), we automatically compared the hotels listed on both websites. The result was 20,880 hotels that matched on both websites, the missing values were eliminated from all variables and the final result was 19,660 hotels. In order to avoid possible bias, only cities with at least 30 hotels and hotels with at least 30 reviews on Booking.com and on TripAdvisor were selected, so, a total of 13,899 hotels were analyzed, as shown in Table 1.

The statistical calculations were performed using R version 3.2.1.

Table 1. Sample selection

	Booking.com	TripAdvisor
Destinations	447	451
Hotels	40,580	69,997
Hotels on both websites	19,660	19,660
Total reviews	11,871,134	8,812,826
Min. Review	5	1
Max. Review	18,120	16,750

Source: Compiled by the authors based on data from Booking.com and TripAdvisor

In order to check the hypothesis, we defined a linear model for the score on TripAdvisor (Ar) and Booking.com (Br) versus the number of reviews on TripAdvisor (Aw) and Booking.com (Bw) as:

$$\mathrm{Ar} = \mathrm{Aw} \cdot \beta_1 + \epsilon_1 \text{ for TripAdvisor (Eq. 1)}$$

$$\mathrm{Br} = \mathrm{Bw} \cdot \beta_2 + \epsilon_2 \text{ for Booking.com (Eq. 2)}$$

In order to check the hypothesis, it was necessary to estimate whether the linear regression model allowed the score to be inferred and if it was statistically significant. In other words, the null hypothesis and alternative hypothesis could be stated as follows:

$$H1^A_{1\ 0} : \beta_1 = 0$$

$$H1^A_{1\ 1} : \beta_1 \neq 0$$

$$H1^B_{1\ 0} : \beta_2 = 0$$

$$H1^B_{1\ 1} : \beta_2 \neq 0$$

Under the null hypothesis, the following test statistic (Faraway, 2014):

$$F = \frac{\frac{(tss-rss)}{(p-1)}}{\frac{rss}{(n-p)}} \text{ (Eq. 3)}$$

follows a Fisher distribution, where n = (the number of variables), p = 13,899 (number of samples), rss = $\sum_{i=1}^{n}(Ar_i - Aw_i \cdot \beta)$ and tss = $\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{ar_i} - \bar{\mathrm{ar}})$. Here we denote ar_i and aw_i as the sample values of Ar and Aw, respectively, and $\overline{ar}$ the mean value of Ar.

Additionally, we also show the Pearson correlation coefficient in order to determine the strength of the correlation. Missing values were eliminated from both variables to obtain identical pairs.

The test statistic and the Pearson correlation coefficient between Booking.com ranking and reviews adopted expressions analogous to those of TripAdvisor.

4. Results

To check the relationship between the number of reviews posted on Booking.com and TripAdvisor and the scores, the Pearson correlation coefficients were calculated by regions.

By regions, de p-value for the test statistic (Eq. 1 and Eq. 2) is $p < .001$ as can be seen on Table 2, so the null hypothesis is refused confirming the relationship between number of reviews and score on TripAdvisor and on Booking.com (except EUR), the same that happens in some cities.

The results show that the Pearson correlation between both scores and reviews were higher in MEA, especially on TripAdvisor. On Booking.com, there was a very weak relationship between score and reviews in ASP and in MEA. In AME, the correlation was the opposite; a larger number of reviews led to a worse position in the ranking, and in EUR was not statistically significant.

Table 2. Spearman correlation coefficient between ranking and reviews on TripAdvisor and on Booking.com and linear model regression and linear model regression

Region	N	r_S TripAdvisor	F TripAdvisor	β TripAdvisor	r_S Booking.com	F Booking.com	β Booking.com
AME	4,130	-.256*	11.6*	-.053*	.164*	144.5*	.184*
ASP	5,922	-.508*	240.5*	-.198*	-.264*	128.6*	-.146*
EUR	8,809	-.234*	251.8*	-.167*	.020***	27.0*	-.055*
MEA	799	-.354*	58.5*	-.261*	.306*	17.1*	.145*

Note. Coefficients are shown in the table; p-values are $*p < .001$ $**p < .05$ $***p > .05$

Table 3. Spearman correlation coefficient between ranking and reviews on TripAdvisor and linear model regression by cities

City	n	r_S TripAdvisor	F TripAdvisor	β TripAdvisor	R^2 TripAdvisor
Dresden	56	-.889*	43.73*	-.069*	.448*
Bucharest	69	-.886*	53.11*	-.113*	.442*
Medellin	44	-.852*	38.27*	-.123*	.477*
Warsaw	46	-.846*	30.62*	-.026*	.410*
Abu Dhabi	57	-.845*	67.47*	-.050*	.551*
Zermatt	54	-.839*	75.61*	-.742*	.666*
Yogyakarta	67	-.834*	53.67*	-.104*	.452*
Salvador	51	-.830*	27.35*	-.043*	.358*
Bogota	117	-.829*	63.01*	-.181*	.354*
Cairo	50	-.829*	44.41*	-.060*	.481*
Jakarta	172	-.826*	107*	-.272*	.386*
Krakov	78	-.826*	71.44*	-.096*	.485*
Dubai	211	-.824*	184.4*	-.146*	.469*
Lima	96	-.821*	64.9*	-.078*	.408*
Seoul	162	-.807*	86.38*	-.183*	.351*
Sao Paulo	131	-.813*	185.041	-.154*	.483*
Hue	45	-.779*	30.81*	-.038*	.417*
Hanoi	205	-.775*	56.13*	-.110*	.217*
Nha Trang	83	-.713*	32.8*	-.093*	.288*
Da Nang	75	-.710*	42.06*	-.180*	.366*
Hangzhou	77	-.673*	18.69*	-.802*	.198*
Chicago	80	-.066***	.01***	-.00***	.000***
New York C.	235	-.137**	.19***	.00***	.001***

Note. Coefficients are shown in the table; p-values are $*p < .001$ $**p < .05$ $***p > .05$

Table 4. Spearman correlation coefficient between ranking and reviews on Booking.com and linear model regression by cities

City	n	r_s Booking.com	F Booking.com	β Booking.com	R^2 Booking.com
Dresden	56	-.236***	1.44***	-.003***	.026***
Bucharest	69	-.309**	1.26***	-.012***	.018***
Medellin	44	-.201***	.76***	-.012***	.018***
Warsaw	46	-.388*	5.06**	-.004**	.103**
Zermatt	54	-.000***	.007***	-.001***	.000***
Abu Dhabi	57	-.457*	11.44*	-.007*	.172*
Yogyakarta	67	-.513*	19.04*	-.085*	.227*
Salvador	51	-.485*	11.33*	-.027*	.188*
Bogota	117	-.239**	3.52***	-.052***	.030***
Cairo	50	-.479*	9.25*	-.018*	.162*
Jakarta	172	-.483*	29.73*	-.116*	.149*
Krakov	78	-.321**	5.67**	-.020**	.070**
Dubai	211	-.495*	57.94*	-.034*	.217*
Lima	96	-.607*	29.07*	-.086*	.236*
Seoul	162	-.651*	79.07*	-.235*	.331*
Sao Paulo	131	-.214**	7.15*	-0.03*	.053*
Hue	45	-.733*	28.76*	-.047*	.401*
Hanoi	205	-.643*	72.78*	-.231*	.264*
Nha Trang	83	-.773*	57.67*	-.229*	.416*
Da Nang	75	-.711*	25.87*	-.209*	.262*
Hangzhou	78	-.637*	16.39*	-.141*	.177*
Chicago	80	.376*	9.38*	.013**	.107**
New York C.	235	.247*	15.03*	.000*	.061*

Note. Coefficients are shown in the table; p-values are $*p < .001$ $**p < .05$ $***p > .05$

At the bottom of the ranking are some major cities, such as New York City or Chicago, which had a weak inverse correlation between online reviews and scores on Booking.com, indicating that the higher the number of reviews, the worse the score was. On TripAdvisor, Chicago and New York City did not show any statistical significance.

To check whether the quantity of reviews influences the score, a simple linear model was calculated. By regions, the results show a very weak explanatory power on TripAdvisor (Adj. R^2 between .056 and .210), and on Booking.com (Adj. R^2 between .005 and .021), statistically significant $p < .001$.

Again, by cities, the previous simple linear regression to predict score on TripAdvisor and on Booking.com based on number of reviews on TripAdvisor and on Booking.com, respectively, was calculated.

The results show that the number of reviews on TripAdvisor and on Booking.com predicted the score on these website, but only in certain cases.

On TripAdvisor, the cities with a higher R^2 were Vancouver, Yogyakarta, Sorrento, Kochi, Dublin, and Zermatt, as shown in Table 3.

Cohen (1988) suggested R^2 values as follows: 0.26 (substantial), 0.13 (moderate) and 0.02 (weak). Only R^2 of 12 cities (1 in AME, 4 in ASP, 4 in EUR, and 3 in MEA) are considered substantial and statistically significant, and as a result of that, the power of the reviews on TripAdvisor in explaining the score. On Booking.com, only 2 cities from ASP had a $R^2 \geq .26$.

As shown in Table 4, the cities with a higher R^2 on Booking.com were Nha Trang, Hue, and Seoul.

As an example, for hotels in Vancouver, the results of the regression indicate that the predictor (number of reviews on TripAdvisor) explains 39.7% of the variance ($F_{(1,48)}$=30.35, $p < .001$).

Therefore, the results partially confirm the hypothesis that the larger the number of reviews, the better score is on TripAdvisor but not on Booking.com.

5. Discussion

Referring to the hypothesis, we concluded that it was partially confirmed. From the entire data set, a stronger correlation was observed on TripAdvisor than on Booking.com and, from the data split by regions, the correlation coefficient was higher in MEA than in ASP, EUR, and AME on TripAdvisor, and on Booking.com the coefficient was higher in ASP but weak.

Depending on the cities analyzed, the behavior was different. Hence, destinations such as Vancouver, Abu Dhabi, or Yogyakarta had a statistically significant correlation coefficient above 0.6 on TripAdvisor. In these cases, the results therefore indicate a relationship between the quantity of reviews and the score.

More than 100 cities of the total analyzed show a statistically significant correlation coefficient above 0.26 on TripAdvisor, and only 47 cities on Booking.com.

By cities, the results show that the explanatory power of the model is lower on Booking.com than on TripAdvisor; very few cities explain that the number of reviews predicts the scores on Booking.com, only Nha Trang and Hue show that the number of reviews explained the 46% and the 33% of the variance, respectively, and are statistically significant.

The results confirm some relationship between the amount of reviews and the score on TripAdvisor, as pointed out by Melian-Gonzalez et al. (2013), who suggested that the more reviews there are, the higher the score is. However, in this study we point out that this trend is not the case worldwide, and that scores do not behave in the same way, as the score on TripAdvisor has a stronger relationship with the reviews than on Booking.com. By regions, the correlation in MEA is higher in both websites than in the rest of the regions.

Given the theory of eWOM that volume counts more than valence (Liu, 2006) and that positive eWOM generates positive attitudes and increases sales opportunities, (Hong, 2006; Karakaya & Barnes, 2010; Lee et al., 2008; Pantelidis, 2010; Steffes & Burgee, 2013; Susskind, 2002; Vermeulen & Seegers, 2009; Ye et al., 2009), with this research we close the triangle confirming that on TripAdvisor there is also a relationship between volume and score and rejecting that, in general, on Booking.com there is such relationship. It could be explained because on this website the reviews that are older than 24 months are not taken into account to calculate the hotel's score, and the conclusion pointed by Melian et al. (2013: 279) that "as the number of reviews of a hotel increases, the ratings are more positive", with the elimination of the oldest reviews on Booking.com, the possible balancing effect of the valence, disappears.

Moreover, there are other items that influence the overall score on the websites such as hotel management if it is part of a chain or is independent (Banerjee & Chua, 2016), the room price (Martin-Fuentes, 2016; Öğüt & Onur Taş, 2012) or the hotel category (Martin-Fuentes, 2016).

6. Conclusions

This study contributes to the hospitality literature by explaining that the behavior in the relationship between the number of reviews and the score differs from one website to the other, and for one city to the other. To encourage customers to write reviews on COPs or on other websites about their experience cannot be guaranteed always as a good result on the scores and it is not possible to be sure that the relationship between online travel reviews and score is a question of cause-effect (Mellinas Cánovas, 2015).

Keeping the old reviews to get the score of a hotel causes that the scores tend to be more positive but, on the other hand, does not show the current reality of hotels, instead, Booking.com deletes old reviews, which allows obtaining an overall score that is closer to the recent situation.

Acknowledgements

This work was partially funded by the Spanish Ministry of the Economy and Competitiveness: research project TIN2015-71799-C2-2-P and ENE2015-64117-C5-1-R.

This research article has received a grant for its linguistic revision from the Language Institute of the University of Lleida (2016 call).

7. References

Anderson, C. K. (2012). The Impact of Social Media on Lodging Performance. *Cornell Hospitality Report*, *12*(15), 4–11. Retrieved from http://www.budigitalhub.com/sites/default/files/white_papers/HotelsSocialMedia.pdf

Anderson, E. W. (1998). Customer Satisfaction and Word of Mouth. *Journal of Service Research*, *1*(1), 5–17. http://doi.org/10.1177/109467059800100102

Arndt, J. (1967). Role of product-related conversations in the diffusion of a new product. *Journal of Marketing Research*, 291–295. JOUR.

Ayeh, J. K., Au, N., & Law, R. (2013). "Do We Believe in TripAdvisor?" Examining Credibility Perceptions and Online Travelers' Attitude toward Using User-Generated Content. *Journal of Travel Research*, *52*, 437–452. http://doi.org/10.1177/0047287512475217

Baka, V. (2016). The becoming of user-generated reviews: Looking at the past to understand the future of managing reputation in the travel sector. *Tourism Management*, *53*, 148–162. http://doi.org/10.1016/j.tourman.2015.09.004

Banerjee, S., & Chua, A. Y. K. (2016). In search of patterns among travellers' hotel ratings in TripAdvisor. *Tourism Management*, *53*, 125–131. http://doi.org/10.1016/j.tourman.2015.09.020

Barreda, A., & Bilgihan, A. (2013). An analysis of user-generated content for hotel experiences. *Journal of Hospitality and Tourism Technology*, *4*(3), 263–280. JOUR. http://doi.org/10.1108/JHTT-01-2013-0001

Booking.com. (2016). About Booking.com. Retrieved September 23, 2016, from http://www.booking.com/content/about.en-gb.html

Boyd, D. E., Clarke, T. B., & Spekman, R. E. (2014). The emergence and impact of consumer brand empowerment in online social networks: A proposed ontology. *Journal of Brand Management*, *21*(6), 516–531. http://doi.org/10.1057/bm.2014.20

Burton, J., & Khammash, M. (2010). Why do people read reviews posted on consumer-opinion portals? *Journal of Marketing Management*, *26*(3–4), 230–255. JOUR.

Butler, R. W. (1980). The concept of a tourist area cycle of evolution: Implications for management of resources. *The Canadian Geographer/Le Géographe Canadien*, *24*(1), 5–12. http://doi.org/10.1111/j.1541-0064.1980.tb00970.x

Cantallops, A. S., & Salvi, F. (2014). New consumer behavior: A review of research on eWOM and hotels. *International Journal of Hospitality Management*, *36*, 41–51. JOUR.

Casaló, L. V., Flavián, C., Guinalíu, M., & Ekinci, Y. (2015). Do online hotel rating schemes influence booking behaviors? *International Journal of Hospitality Management*, *49*, 28–36. http://doi.org/10.1016/j.ijhm.2015.05.005

Chen, Y.-F., & Law, R. (2016). A Review of Research on Electronic Word-of-Mouth in

Hospitality and Tourism Management. *International Journal of Hospitality & Tourism Administration*, *17*(4), 347–372. http://doi.org/10.1080/15256480.2016.1226150

Cohen, E. (1972). Toward a sociology of international tourism. *Social Research*, 164–182. JOUR.

Cohen, J. (1988). Statistical power analysis for the behavioural sciences. Hillside. *NJ: Lawrence Earlbaum Associates*. JOUR.

Dellarocas, C., Zhang, X. (Michael), & Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing*, *21*(4), 23–45. http://doi.org/10.1002/dir.20087

Duan, W., Gu, B., & Whinston, A. B. (2008). The dynamics of online word-of-mouth and product sales—An empirical investigation of the movie industry. *Journal of Retailing*, *84*(2), 233–242. http://doi.org/10.1016/j.jretai.2008.04.005

Faraway, J. J. (2014). *Linear models with R*. BOOK, CRC Press.

Godes, D., & Mayzlin, D. (2004). Using Online Conversations to Study Word-of-Mouth Communication. *Marketing Science*, *23*(4), 545–560. http://doi.org/10.1287/mksc.1040.0071

Gretzel, U., & Yoo, K. H. (2008). Use and Impact of Online Travel Reviews. In P. O'Connor, W. Höpken, & U. Gretzel (Eds.), *Information and Communication Technologies in Tourism* (pp. 35–46). Vienna: Springer Vienna. http://doi.org/10.1007/978-3-211-77280-5_4

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? *Journal of Interactive Marketing*, *18*(1), 38–52. http://doi.org/10.1002/dir.10073

Hong, T. (2006). The influence of structural and message features on Web site credibility. *Journal of the American Society for Information Science and Technology*, *57*(1), 114–127. http://doi.org/10.1002/asi.20258

Jeacle, I., & Carter, C. (2011). In TripAdvisor we trust: Rankings, calculative regimes and abstract systems. *Accounting, Organizations and Society*, *36*(4–5), 293–309. http://doi.org/10.1016/j.aos.2011.04.002

Karakaya, F., & Barnes, N. G. (2010). Impact of online reviews of customer care experience on brand or company selection. *Journal of Consumer Marketing*, *27*(5), 447–457. http://doi.org/10.1108/07363761011063349

Lee, J., Park, D.-H., & Han, I. (2008). The effect of negative online consumer reviews on product attitude: An information processing view. *Electronic Commerce Research and Applications*, *7*(3), 341–352. http://doi.org/10.1016/j.elerap.2007.05.004

Litvin, S. W., Goldsmith, R. E., & Pan, B. (2008). Electronic word-of-mouth in hospitality and tourism management. *Tourism Management*, *29*(3), 458–468. http://doi.org/10.1016/j.tourman.2007.05.011

Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing*, *70*(3), 74–89. JOUR.

Martin-Fuentes, E. (2016). Are guests of the same opinion as the hotel star-rate classification system? *Journal of Hospitality and Tourism Management*, *29*, 126–134. http://doi.org/10.1016/j.jhtm.2016.06.006

Mayzlin, D., Dover, Y., & Chevalier, J. A. (2012). *Promotional reviews: An empirical investigation of online review manipulation* (RPRT). National Bureau of Economic Research.

Melian-Gonzalez, S., Bulchand-Gidumal, J., & Gonzalez Lopez-Valcarcel, B. (2013). Online Customer Reviews of Hotels: As Participation Increases, Better Evaluation Is Obtained. *Cornell Hospitality Quarterly*, *54*(3), 274–283. http://doi.org/10.1177/1938965513481498

Mellinas Cánovas, J. P. (2015). *Análisis y aplicaciones de los sistemas de medición de la reputación online de los hoteles*. Universidad Politécnica de Cartagena.

Memarzadeh, F., Blum, S. C., & Adams, C. (2015). The impact of positive and negative e-comments on business travelers' intention to purchase a hotel room. *Journal of Hospitality and Tourism Technology*, *6*(3), 258–270. http://doi.org/10.1108/JHTT-09-2014-0049

Morgan, N. J., Pritchard, A., & Piggott, R. (2003). Destination branding and the role of the stakeholders: The case of New Zealand. *Journal of Vacation Marketing*, *9*, 285–299. JOUR.

O'Connor, P. (2008). User-Generated Content and Travel : A Case Study on Tripadvisor.Com. *Business*, *21*, 47–58. http://doi.org/10.1007/978-3-211-77280-5_5

O'Connor, P. (2010). Managing a Hotel's Image on TripAdvisor. *Journal of Hospitality Marketing & Management*. http://doi.org/10.1080/19368623.2010.508007

Öğüt, H., & Onur Taş, B. K. (2012). The influence of internet customer reviews on the online sales and prices in hotel industry. *The Service Industries Journal*, *32*(2), 197–214. http://doi.org/10.1080/02642069.2010.529436

Pan, B., MacLaurin, T., & Crotts, J. C. (2007). Travel blogs and the implications for destination marketing. *Journal of Travel Research*, *46*(1), 35–45. JOUR.

Pantelidis, I. S. (2010). Electronic Meal Experience: A Content Analysis of Online

Restaurant Comments. *Cornell Hospitality Quarterly*, *51*(4), 483–491. http://doi.org/10.1177/1938965510378574

Park, D.-H., Lee, J., & Han, I. (2007). The Effect of On-Line Consumer Reviews on Consumer Purchasing Intention: The Moderating Role of Involvement. *International Journal of Electronic Commerce*, *11*(4), 125–148. http://doi.org/10.2753/JEC1086-4415110405

Ratcliff, J. W., & Metzener, D. E. (1988). Pattern-matching-the gestalt approach. *Dr Dobbs Journal*, *13*(7), 46. JOUR.

Sigala, M. (2008). Web 2.0, social marketing strategies and distribution channels for city destinations. In G.-H. & Torres-Coronas (Ed.), *Information Communication Technologies and City Marketing* (pp. 220–244). Hershey, New York, USA: Information Science Reference.

Sparks, B. A., & Browning, V. (2011). The impact of online reviews on hotel booking intentions and perception of trust. *Tourism Management*, *32*(6), 1310–1323. JOUR.

Steffes, E. M., & Burgee, L. E. (2013). Social ties and online word of mouth. Retrieved from http://www.emeraldinsight.com/doi/abs/10.1108/10662240910927812#.VFZYq3xBx7s.mendeley

Sun, S., Fong, L. H. N., Law, R., & Luk, C. (2015). An Investigation of Gen-Y's Online Hotel Information Search: The Case of Hong Kong. *Asia Pacific Journal of Tourism Research*, 1–14. http://doi.org/10.1080/10941665.2015.1062405

Susskind, A. (2002). I told you so! Restaurant customers' word-of-mouth communication patterns. *The Cornell Hotel and Restaurant Administration*

Quarterly, *43*(2), 75–85. http://doi.org/10.1016/S0010-8804(02)80034-9

TripAdvisor. (2016). Retrieved August 5, 2016, from https://www.tripadvisor.com/PressCenter-c6-About_Us.html

Vermeulen, I. E., & Seegers, D. (2009). Tried and tested: The impact of online hotel reviews on consumer consideration. *Tourism Management*, *30*(1), 123–127. http://doi.org/10.1016/j.tourman.2008.04.008

Viglia, G., Furlan, R., & Ladrón-de-Guevara, A. (2014). Please, talk about it! When hotel popularity boosts preferences. *International Journal of Hospitality Management*, *42*, 155–164. http://doi.org/10.1016/j.ijhm.2014.07.001

Wathieu, L., Brenner, L., Carmon, Z., Chattopadhyay, A., Wertenbroch, K., Drolet, A., … Ratner, R. K. (2002). Consumer control and empowerment: A primer. *Marketing Letters*, *13*(3), 297–305. JOUR.

Wilson, T. (2012). Hotels as Ready-to-Hand Recreation: TripAdvisors Posting Potentiality-for-Being in Play. *Tourist Studies*, *12*(1), 70–86. http://doi.org/10.1177/1468797612444198

Xie, K. L., Zhang, Z., & Zhang, Z. (2014). The business value of online consumer reviews and management response to hotel performance. *International Journal of Hospitality Management*, *43*, 1–12. http://doi.org/10.1016/j.ijhm.2014.07.007

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

Ye, Q., Law, R., Gu, B., & Chen, W. (2011). The influence of user-generated content on traveler behavior: An empirical investigation on the effects of e-word-of-mouth to hotel online bookings. *Computers in Human Behavior*, *27*(2), 634–639.

http://doi.org/10.1016/j.chb.2010.04.014

Yen, C.-L. (Alan), & Tang, C.-H. (Hugo). (2015). Hotel attribute performance, eWOM motivations, and media choice. *International Journal of Hospitality Management*, *46*, 79–88. http://doi.org/10.1016/j.ijhm.2015.01.003

Zhang, Z., Zhang, Z., Wang, F., Law, R., & Li, D. (2013). Factors influencing the effectiveness of online group buying in the restaurant industry. *International Journal of Hospitality Management*, *35*, 237–245. http://doi.org/10.1016/j.ijhm.2013.06.012

Zhu, F., & Zhang, X. (2010). Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of Marketing*, *74*(2), 133–148. JOUR.

6. Are guests of the same opinion as the hotel star-rate classification system?

Pages 75 to 95 contain this article:

Martin-Fuentes, E. (2016). Are guests of the same opinion as the hotel star-rate classification system? *Journal of Hospitality and Tourism Management*, *29*, 126–134. http://doi.org/10.1016/j.jhtm.2016.06.006

Journal Metrics
Scopus
CiteScore: 1.97
Source Normalized Impact per Paper (SNIP): 0.977
SCImago Journal Rank (SJR): 0.723
Year 2015 First Quartile / Year 2016 Second Quartile
Area: Business, Management and Accounting Rank 297 of 1,394
Subject area: Tourism, Leisure and Hospitality Management Rank 26 of 84
Social Science Citation Index (SSCI), Journal Citation Report from V26 2016:
https://www.journals.elsevier.com/journal-of-hospitality-and-tourism-management/news/jhtm-to-receive-its-impact-factor

Journal of Hospitality and Tourism Management 29 (2016) 126–134

ELSEVIER

Contents lists available at ScienceDirect

Journal of Hospitality and Tourism Management

journal homepage: http://www.journals.elsevier.com/journal-of-hospitality-and-tourism-management

Are guests of the same opinion as the hotel star-rate classification system?

Eva Martin-Fuentes

Department of Business Administration, University of Lleida, C/ Jaume II, 73, 25001, Lleida, Spain

A R T I C L E I N F O

Article history:
Received 30 March 2016
Received in revised form
28 May 2016
Accepted 21 June 2016

Keywords:
eWOM
Star-rate system
Room price
Hotel size
Booking
TripAdvisor

A B S T R A C T

Hotel classification systems have been questioned on some occasions due to the loss of credibility of stars as a quality standard and because they are sometimes subject to outdated criteria. In any case, this system allows reducing the adverse effects of asymmetric information, characterized in a market such as the hospitality industry.

With a sample of more than 14,000 hotels in 100 cities around the world taken from two of the most important tourism websites as are Booking and TripAdvisor, we ascertained whether the star-rating classification system of hotels, room price, or even hotel size, match user satisfaction measured from the point of view the scores awarded by past users.

The results confirm that despite the differences in criteria in implementing the hotel star-rate classification system throughout the world, a relationship does exist with user satisfaction, based on the scores awarded by former customers both on TripAdvisor and on Booking. In turn, price is related to hotel category and with satisfaction. However, the number of rooms does not influence the score awarded, although depending on the region, there is a relationship between hotel size and category.

We conclude that the hotel classification system adequately fulfils its function as customer ratings increase with each additional star, just as price is also related with both aspects.

The main contribution of this study is that the results concern hotels from around the world comparing them with the views of customers expressed on TripAdvisor and Booking.

6.1. Introduction

Recent studies related to the accommodation sector have shown that future guests rely on recommendations by friends and family to solve their informational disadvantage, as tourism services cannot be tried or tested before purchasing them (Fernández-Barcala et al., 2010). On certain occasions, the role of travel agents replaces that of friends and family, since they act as an intermediary in a market characterized by such asymmetry (Clerides, Nearchou, & Pashardes, 2005; Jeacle & Carter, 2011).

Moreover, online reviews are also a source of information for travelers that perceive UGC as being similar to their relatives' recommendations, relying on it more than on the official information provided by firms (Pan, MacLaurin, & Crotts, 2007), especially when such recommendations are posted to popular online communities of travelers such as TripAdvisor (Casalo, Flavian, Guinaliu, & Ekinci, 2015).

Hotel classification systems also allow the adverse effects of asymmetric information to be mitigated (Nicolau & Sellers, 2010; Öğüt & Onur Taş, 2012) in a market such as the hospitality industry.

Furthermore, the star-rating system can be a predictor of room prices (Israeli, 2002), and it is traditionally used to rate hotel quality. Hotel size has been also related to prices, and it has been concluded that larger hotels demand higher prices (Israeli, 2002) and that hotel categories significantly affect the sensitivity of room prices to customer ratings (Öğüt & Onur Taş, 2012).

The aim of this study is to confirm whether the star-rating classification system of hotels determined by a third party, the price of a room fixed by the supply side, or even the hotel size measured in terms of its number of rooms, coincide with users' ratings on two of the main websites used by the hospitality industry (Booking.com and TripAdvisor) in the hotels of the 100 top city tourist destinations according to the Euromonitor Ranking (Geerts, 2016).

6.2. Contribution to the state-of-the-art

The most important finding of this paper is that despite the differences in criteria in implementing the hotel star-rating classification system worldwide, a relationship does exist with scores awarded by former customers both on TripAdvisor and on Booking.com.

Moreover, price is related to hotel category and with users' scores. However, the number of rooms does not influence the score awarded but, depending on the region, there is a relationship between hotel size and category.

The main conclusion of this study is that the hotel classification system adequately fulfils its function as customer ratings increase with each additional star, just as price is also related to both aspects.

6.3. Journal paper

Are guests of the same opinion as the hotel star-rate classification system?

Eva Martin-Fuentes*
Departament of Business Administration
University of Lleida. C/ Jaume II, 73. 25001 LLEIDA (Spain)
E-mail: eva@aegern.udl.cat
*corresponding author

Abstract

Hotel classification systems have been questioned on some occasions due to the loss of credibility of stars as a quality standard and because they are sometimes subject to outdated criteria. In any case, this system allows reducing the adverse effects of asymmetric information, characterized in a market such as the hospitality industry.

With a sample of more than 14,000 hotels in 100 cities around the world taken from two of the most important tourism websites as are Booking and TripAdvisor, we ascertained whether the star-rating classification system of hotels, room price, or even hotel size, match user satisfaction measured from the point of view the scores awarded by past users.

The results confirm that despite the differences in criteria in implementing the hotel star-rate classification system throughout the world, a relationship does exist with user satisfaction, based on the scores awarded by former customers both on TripAdvisor and on Booking. In turn, price is related to hotel category and with satisfaction. However, the number of rooms does not influence the score awarded, although depending on the region, there is a relationship between hotel size and category.

We conclude that the hotel classification system adequately fulfils its function as customer ratings increase with each additional star, just as price is also related with both aspects.

The main contribution of this study is that the results concern hotels from around the world comparing them with the views of customers expressed on TripAdvisor and Booking.

Keywords: eWOM, star-rate system, room price, hotel size, Booking, TripAdvisor

Highlights (3-5)

- Customer satisfaction coincides with the hotel star-rate classification system.
- A relationship exists between customer satisfaction, hotel price and classification.
- There is no relationship between satisfaction and number of hotel rooms.
- The conclusions are taken from the analysis of a large number of hotels (over 14,000) in 100 cities around the world.

1. Introduction

In a market in which one of the parties involved in a buying/selling transaction does not have the same information as the other concerning a product or service, so-called information asymmetry occurs (Akerlof, 1970). In the services, given their intangible nature, it is difficult to evaluate their quality (Zeithaml, Berry, & Parasuraman, 1993).

Recent studies related with the hospitality industry indicate that the prospective customers of a hotel rely on recommendations by friends and family to solve their informational disadvantage because tourism services cannot be tried or tested before purchase (Fernández-Barcala, González-Díaz, & Prieto-Rodríguez, 2010) and that has been substituted, on certain occasions, by the role of the travel agent, who acts as an intermediary in a market characterized by this asymmetry (Clerides, Nearchou, & Pashardes, 2005; Jeacle & Carter, 2011).

The phenomenon of recommendations is especially important with the Internet and is known as electronic Word of Mouth (eWOM) and is defined by Litvin, Goldsmith, & Pan, (2008) as being "all informal communications directed at consumers through Internet-based technology related to the usage or characteristics of particular goods and services, or their sellers".

eWOM, thanks to web-based consumer opinion platforms (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004), can have a significant influence on travel-related decisions (Gretzel & Yoo, 2008) and both positive and negative reviews have the potential to influence customer purchase decisions (Sparks & Browning, 2011). The web-based consumer opinion platforms can also contribute to attenuating the negative effects of asymmetric information, perhaps such as opportunistic behaviours on the part of the supply side.

Information asymmetry can be compensated using other elements such as price, the star-rate classification system (Nicolau & Sellers, 2010; Öğüt & Onur Taş, 2012), customer review ratings, number of recommendations and average display rank (Cezar & Ögüt, 2016).

The aim of this research is to confirm whether, indeed, such elements as the star-rated classification system of hotels determined by a third party, the price of a room fixed by the supply side, or even hotel size, match user satisfaction measured from the point of view of the ratings obtained by past users' scores on two of the main websites used by the hospitality industry (Booking and TripAdvisor) in the hotels of the 100 top city tourist destinations.

This introduction is followed by a review of the existing literature on the subject and the study objectives are set out. Then the methodology is presented, paying special attention to data collection, the results are put forward, leading finally to a section for discussion and conclusions.

2. Literature review and research aims

The review of the literature is divided into three sections. On the one hand the standard system of hotel categories is analysed, while on the other, the importance of electronic Word of Mouth in the hospitality industry is studied, and finally, the existing studies are shown on the relationship between hotel price and size with the star-rating system.

2.1. Standard system of hotel categories

Hotel ratings are used to classify hotels according to their quality using laws approved by national or local governments, or by applying criteria established by independent organizations, hotel associations, national consumer travel organizations, guidebooks, travel websites and volunteer organizations (Denizci Guillet & Law, 2010). Thus, rating systems can be classified into official and non-official (Zhan-Qing & Liu, 1993). The hotel star-rating classification is universally recognized and the most common system for classifying hotels is from 1 to 5 stars.

The system for classifying hotels is different in each country and even hotels from the same country follow different criteria because there are local regulations, like in Spain where the autonomous governments are empowered to legislate in this regard and use different criteria to assign stars to the hotels.

On an international level, there is no common standard concerning what a hotel from each category should provide. What seems clear is that obtaining different stars is based on objective criteria such as infrastructure, services, amenities, and the sizes of the rooms and common spaces.

As Fang, Ye, Kucukusta, & Law, (2016) point out, the overall quality of hotels can be inferred from their stars that are assessed by an official organization according to a unified standard, and hotel star-rating is most often employed by consumers in their choice of hotel (Núñez-Serrano, Turrión, & Velázquez, 2014) and the star-rating classification mechanism is the most common customer segmentation pattern in the hotel industry (Dioko, So, & Harrill, 2013). Additionally, a higher star-rating can be considered as being an indicator of higher quality (Abrate, Capriello, & Fraquelli, 2011) and can be useful to reduce the adverse effects of asymmetric information (Nicolau & Sellers, 2010; Öğüt & Onur Taş, 2012).

Moreover, a study carried out by Bulchand-Gidumal, Melián-González, & González López-Valcárcel, (2011) with a data from more than 10,000 hotels from TripAdvisor, confirmed that each additional star enhances a hotel's score.

Not all research studies confirm the relation between the star-rating classification system and quality. According to Núñez-Serrano et al., (2014) there has been a deterioration and loss of the reliability of the star-rating system as a quality standard, from their analysis of 7,783 hotels from the Official Guide to Hotels in Spain (OGHS).

A study conducted by Torres, Adler, & Behnke, (2014) confirmed that there were powerful reasons why hotel rating systems might become obsolete, an opinion expressed by General Managers interviewed in their research.

Furthermore, López Fernández & Serrano Bedia, (2004) conclude in their study consisting of personal interviews with customers from 54 hotels in Cantabria, Spain, that there are significant differences between expectations, perceptions and the various hotel categories, so the ranking of the groups does not correspond with the categories.

To find out whether the hotel star-rating classification system determined by the supply side or by a third party that is different all over the world has a relationship with customer satisfaction measured by votes in the form of ratings in two of the main websites used by the hospitality industry (Booking and TripAdvisor), the following research hypothesis is posited:

> H1. The higher (lower) the category of hotel, the better (worse) the score and, therefore, the better (worse) the position in the ranking.

2.2. Electronic Word of Mouth

In services, the importance of recommendations, known as Word of Mouth (WOM), has been widely discussed by many researchers (Butler, 1980; Cohen, 1972; Dellarocas, 2003; Hu, Bose, Gao, & Liu, 2011; Liu, 2006) and WOM occurring in digital environments, known as electronic Word of Mouth (eWOM) is especially important because of the magnitude recommendations can acquire.

According to Cantallops & Salvi (2014), research on eWOM in the hotel industry can be divided into two groups: review-generating factors (previous factors that cause consumers to write reviews) and impacts of eWOM (impacts caused by online reviews) from the consumer perspective and the company perspective.

eWOM influences travel-related decisions and consumers' reviews generate more trust than communications from the company itself (Gretzel & Yoo, 2008). Positive eWOM increases the probability of booking a room in a hotel (Vermeulen & Seegers, 2009), leading to an increase in the rooms sold for each additional point on the TripAdvisor rating scale (Anderson, 2012) or a 10 percent increase in traveller review ratings boosting online bookings by more than 5 percent (Ye, Law, Gu, & Chen, 2011), resulting in a better conversion rate (Petz & Greiner, 2014) and high numbers of recommendations increase online hotel room sales (Cezar & Ögüt, 2016), while negative eWOM generates the opposite effect (Hong, 2006; Karakaya & Barnes, 2010; Lee, Park, & Han, 2008; Steffes & Burgee, 2013).

For some authors, positive or negative eWOM is not the only important element of this phenomenon. Also important is the number of reviews (Viglia, Furlan, & Ladrón-de-Guevara, 2014), giving belief to the theory that volume is more important than valence (Liu, 2006) and stating that a large number of reviews may encourage potential consumers to decide to buy a product that many other people have also acquired (Dellarocas, Zhang, & Awad, 2007; Godes & Mayzlin, 2004; Park, Lee, & Han, 2007) and because it is a sign of popularity (Zhang, Zhang, Wang, Law, & Li, 2013 and Zhu & Zhang, 2010 cited in Xie, Zhang, & Zhang, 2014).

2.3. Room price and hotel size

Hotels upgrade to higher star categories, thereby generating more revenue (Leung, Lee, & Law, 2011) because the hotel star-rating system has the most significant impact on price dispersion, and hotels with a higher star-rating can charge more flexible room rates (Zong, Tang, Huang, & Ma, 2008).

Research conducted in Israel demonstrates that the star-rating system is still a stable and consistent predictor of room prices (Israeli, 2002), and it is traditionally used to rate hotel quality. Abrate & Viglia, (2016) have identified three groups of variables that are based on dynamic pricing which are: tangible (physical attributes), reputational (stars and online) and contextual (booking time, free cancellation, competition).

As pointed out by Ben Aissa & Goaied (2016), there is also a growing body of literature investigating the relationship between hotel size and hotel financial performance leading to different findings.

A study comparing hotels from London and Paris on Booking reveal that the star-rating of hotels significantly affects the sensitivity of room prices to customer ratings, as less price-sensitive customers value quality higher (Öğüt & Onur Taş, 2012).

Some studies have investigated with hedonic price methods the relationship with quality in the hospitality industry (Chen & Rothschild, 2010; Hamilton, 2007; Masiero, Nicolau, & Law, 2015; Monty & Skidmore, 2003). Some results show that the most relevant characteristics are cleanliness, location and facilities in the 8,000 hostels analysed worldwide (de Oliveira Santos, 2016) or revealing price differences between hotels depending on the category (Saló, Garriga, Rigall-i-Torrent, Vila, & Fluvià, 2014).

Noting that the hotel classification system can be a predictor of room rates gives rise to hypothesis:

> H2a. The higher (lower) the hotel category, the higher (lower) the price of the room.

Furthermore, observing that quality signals have a positive effect on price setting (Abrate et al., 2011) and that factors associated with consumer sensitivity to price are gaining importance in research (Cantallops & Salvi, 2014), hypothesis posits

> H2b the higher (lower) the price of the room, the better (worse) score and therefore the better (worse) position in the ranking generated by the ratings of past guests.

Moreover, according to research conducted in the Israeli hospitality industry, the results indicate that star information is perceived as more relevant for pricing than brand name (Danziger, Israeli, & Bekerman, 2006), and the number of rooms per hotel was also significant, suggesting that larger hotels demanded higher prices (Israeli, 2002).

As pointed out by Claver-Cortés, Molina-Azorín, & Pereira-Moliner, (2007), various studies have classified hotels according to their size (Baum & Mezias, 1992; Chung & Kalnins, 2001; Ingram, 1996; Lant & Baum, 1995) and they confirm that size and category are strategic variables to increase hotel performance, together with type of hotel management.

Research analysing hotels on the Costa Brava, Spain, concluded that the effects on price of some characteristics related to location differ for each type of accommodation and other attributes with a significant effect on price are town, hotel size, distance from the beach and availability of parking spaces (Espinet, Saez, Coenders, & Fluvià, 2003).

In addition to studying the relationship with price, we intended to test whether there are other attributes related to hotel category and customer ratings, such as hotel size measured from the point of view of the number of rooms. Hence

> H3a: the higher (lower) the hotel category, the higher (lower) the number of rooms
> H3b: the higher (lower) the number of rooms, the better (worse) the score.

3. Methodology

Having considered the existing literature and given that the price of a hotel room or the number of hotel rooms is set by the service provider, the classification of hotels by stars, in most cases determined by a third party such as official authorities based on existing regulations, or unofficial institutions with objective criteria, the aim of this research is to ascertain whether hotel category, number of rooms and price match user satisfaction measured from the point of view of the opinions expressed by previous customers in two of the most influential businesses in the tourism industry in recent times, which have significant differences in their business models. One, TripAdvisor, a web-based consumer opinion platform, and other, Booking, one of the leading online hotel brokerage companies in the world.

Booking.com B.V., part of the Priceline Group, is world leader in booking accommodation online with 857,403 active properties in 223 countries and territories with over 1,000,000 room nights reserved on Booking.com each day (Booking.com. 2016).

TripAdvisor is one of the most important web-based consumer-opinion platforms (COPs) enabling travellers to plan and book the perfect trip. TripAdvisor-branded sites make up the largest travel community in the world, reaching 350 million unique monthly visitors, and 320 million reviews and opinions covering more than 6.2 million accommodations, restaurants and attractions (TripAdvisor, 2016).

In this study, we analysed the hotels of the Top 100 city tourist destinations in the world, according to the Euromonitor Ranking (Geerts, 2016). The 100 cities were divided into 4 regions following the denominations of Banerjee & Chua, (2016): America (AME), Asia Pacific (ASP), Europe (EUR) and Middle East Africa (MEA).

During February 2016 we collected the information of the hotels from Booking and TripAdvisor (see Table 1): number of reviews, ranking and score on both websites, and from Booking: hotel category, number of rooms and price rank.

We filtered the results by "property type" in Booking as "Hotels" and we selected the review score of Booking with the option rated by "All reviewers". Once gathered, all the hotels of each city were compared with TripAdvisor. On this website we took into account only the type of accommodation "Hotels", discarding other options, and we ordered them according to "Ranking".

The data were collected using a web browser automatically controlled that simulated a user navigation (clicks and selections) for TripAdvisor and Booking. Once the data was available, a new data set was created by joining together corresponding data for a given hotel from both websites. The join criteria used was, for every city: 1) If hotel name was exactly the same. 2) Else if the hotel name from one site was contained, entirely, on the name from the other site (the choosing of container and contained was depending on name length, container chosen as the longest name available). 3) If no match was found, then the Ratcliff/Obershelp (Ratcliff & Metzener, 1988) similarity was computed between each possible pair of names (one from Booking and one from Tripadvisor), the list of distances was then sorted, and the greatest one (best match) was chosen, if that similarity was higher than 0.85 (that is 85% of letters match considering position), the pair was chosen, and the names removed from both lists.

The data collected from each city and platform were taken simultaneously, in order for the score and the number of reviews to undergo the minimum variation, because the websites are active and their data are modified day after day.

The price variable in this study is not an absolute value (currency), but ranges from 1, the cheapest, to 5, the most expensive, these data being obtained from Booking.

Some values were missing from our dataset because not all managers provide hotel category or number of rooms or price, and some properties had not received any ratings by users.

According to the Booking.com B.V. website, "the information disclosed is based on that provided by accommodation providers. As such, the accommodation providers are given access to an extranet through which they are fully responsible for updating all rates, availability and other information which is displayed on the website, even the star classification".

As highlighted in the review of the literature, the star-rating system is different in every country and hence it is difficult to compare hotels from all over the world. For this reason we considered the star-rating provided by Booking as being useful for comparing hotels, as well as price ranking and room numbers provided by Booking used in other research (Öğüt & Onur Taş, 2012).

Moreover, with a random sample of 2.5% of the hotels all from our dataset, the star-rated classifications shown in Booking were checked with the official websites of the hotels and in most cases, 92.1%, the stars matched. Discrepancies were found in hotels from ASP, 3.8%, AME, 2.5% and EUR, 1.6%.

Table 1. Sample data

	Booking	TripAdvisor
Region	4	4
Country	48	48
Destination	100	100
Hotels	49,315	85,274
Hotels on both websites	14,726	14,726
Reviews	8,264,853	6,272,634
Min. Review	5	1
Max. Review	16,300	16,110

Source: Compiled by authors based on data from Booking and TripAdvisor

4. Results

To test H1: The higher (lower) the category of hotel, the better (worse) the score, Spearman's rank correlation test between hotel category and score was conducted for TripAdvisor and Booking.com as hotel category is displayed as a ranking from 1 to 5 stars. This nonparametric test is used to check the first hypothesis because category of hotel is an ordinal qualitative variable and the score is a quantitative variable. The results indicate for the total sample that the correlation between hotel category and score is moderate: 0.4255 ($p < .001$) on Booking and 0.4316 ($p < .001$) on TripAdvisor (see Table 7).

Table 2. Proportional contingency table between ranking brackets and hotel category for Booking and TripAdvisor

Category	1*		2*		3*		4*		5*		Total	
Ranking	TA	Bk	TA	Bk	TA	Bk	TA	Bk	TA	Bk	TA	Bk
1-50	0.00	0.00	0.01	0.01	0.04	0.08	0.07	0.10	0.07	0.08	0.19	0.27
51-100	0.00	0.00	0.01	0.03	0.06	0.09	0.06	0.09	0.02	0.03	0.15	0.24
101-300	0.01	0.01	0.06	0.08	0.16	0.17	0.12	0.10	0.03	0.02	0.38	0.38
>300	0.01	0.00	0.08	0.04	0.12	0.04	0.06	0.02	0.01	0.00	0.28	0.10
Total	**0.02**	**0.01**	**0.16**	**0.16**	**0.38**	**0.38**	**0.31**	**0.31**	**0.13**	**0.13**	**1**	**1**

Source: Compiled by authors based on data from Booking and TripAdvisor

Table 3. Pearson residuals between ranking brackets and hotel category for Booking and TripAdvisor

Category	1*		2*		3*		4*		5*		Total	
Ranking	TA	Bk	TA	Bk	TA	Bk	TA	Bk	TA	Bk	TA	Bk
1-50	-5.38	-6.29	-14.83	-16.7	-13.59	-9.44	4.1	5.36	34.99	29.08	5.29	2.01
51-100	-1.99	-2.1	-9.01	-4.82	-1.02	0.64	6.2	6.11	2.78	-4.2	-3.04	-4.37
101-300	0.67	5.6	0.32	6.81	5.75	7.61	1.25	-4.67	-12.3	-15.69	-4.31	-0.34
>300	5.09	2.59	18.39	20.64	5.21	-0.25	-9.39	-8.77	-16.42	-10.22	2.88	3.99
Total	**-1.61**	**-0.2**	**-5.13**	**5.93**	**-3.65**	**-1.44**	**2.16**	**-1.97**	**9.05**	**-1.03**	**0.82**	**1.29**

Source: Compiled by authors based on data from Booking and TripAdvisor

Table 4. Pearson residuals between price and stars

	1 $	2 $	3 $	4 $	5 $	Total
1*	24.36	30.97	-0.24	-17.19	-12.96	24.94
2*	4.92	20.93	9.36	-14.27	-15.99	4.95
3*	-2.92	1.14	16.14	-6.37	-16.96	-8.97
4*	-6.96	-13.64	5.88	11.32	-10.99	-14.39
5*	-8.79	-21.12	-24.4	14.82	41.68	2.19
Total	**10.61**	**18.28**	**6.74**	**-11.69**	**-15.22**	**8.72**

Source: Compiled by authors based on data from Booking and TripAdvisor

Table 5. Proportional contingency table between ranking brackets and prices for Booking and TripAdvisor

Price	1 $		2 $		3 $		4 $		5 $		Total	
Rank	TA	Bk	TA	Bk	TA	Bk	TA	Bk	TA	Bk	TA	Bk
1-50	0.00	0.01	0.01	0.02	0.02	0.03	0.04	0.07	0.13	0.16	0.20	0.29
51-100	0.01	0.02	0.02	0.03	0.03	0.05	0.05	0.07	0.06	0.07	0.17	0.24
101-300	0.04	0.05	0.07	0.08	0.08	0.09	0.10	0.09	0.08	0.05	0.37	0.37
>300	0.05	0.03	0.07	0.03	0.06	0.02	0.05	0.02	0.03	0.01	0.26	0.11
Total	**0.10**	**0.11**	**0.17**	**0.16**	**0.19**	**0.19**	**0.24**	**0.25**	**0.30**	**0.30**	**1**	**1**

Source: Compiled by authors based on data from Booking and TripAdvisor

Table 6. Pearson residuals between ranking brackets and price ranking for Booking and TripAdvisor

Price	1 $		2 $		3 $		4 $		5 $		Total	
Rank	TA	Bk	TA	Bk	TA	Bk	TA	Bk	TA	Bk	TA	Bk
1-50	-13.05	-12.31	-13.85	-13.27	-11.35	-10.71	-5.31	-1.89	30.24	25.93	-13.32	-12.24
51-100	-7.17	-6.06	-6.15	-2.21	-2.89	1.82	4.54	4.26	6.45	-0.33	-5.22	-2.52
101-300	6.36	11.78	6.13	12.11	6.14	7.67	2.92	-1.13	-15.09	-19.81	6.46	10.62
>300	12.16	13.71	12.47	3.2	5.50	-0.37	-4.36	-2.53	-15.73	-7.22	10.04	6.79
Total	**-1.69**	**7,121**	**-1.40**	**-0.17**	**-2.60**	**-1.59**	**-2.21**	**-1.29**	**5.87**	**-14.24**	**-2.03**	**2.65**

Source: Compiled by authors based on data from Booking and TripAdvisor

Table 8 shows the results for each region analysed and confirms that there is a moderate correlation in all regions: the highest in MEA with 0.53 and 0.57 in TripAdvisor and Booking respectively, and with ASP being the weakest with 0.41 in both portals.

Table 7. Correlations between hotel category, rooms, price, scoring and number of reviews

	Mean	SD	1. [a]	2.	3. [a]	4. [b]	5. [b]	6. [b]	7.
1. Stars	3.45	0.97	1						
2. Rooms	137.96	172.29	0.4834	1					
3. Price	3.54	1.32	0.6757	0.2769 [a]	1				
4. Score TripAdvisor	3.84	0.60	0.4316	0.1000 [b]	0.5320	1			
5. Score Booking	7.86	0.86	0.4255	0.0587 [b]	0.5533	0.7582	1		
6. Reviews TripAdvisor	513.55	784.77	0.3778	0.5140 [b]	0.3436	0.2547	0.2694	1	
7. Reviews Booking	677.51	898.49	0.0961	0.3237 [b]	0.0048**	0.0239*	0.1316	0.4123	1

[a] Spearman rank correlation [b] Pearson correlation
*All p close to 0 except *p < .05; ** p > .05*

Also to test H1: The higher (lower) the category of hotel, the better (worse) position in the ranking, the ranking was divided into four brackets, from positions 1 to 50, from 51 to 100, 101 to 300, and from 301 to the end. As category of hotel is an ordinal qualitative variable, and the position in the ranking is also an ordinal qualitative variable, we conduct a chi-square test for independence.

From chi-square analysis we can see that the probability that in the sample there is the same number of hotels in the different brackets of the TripAdvisor ranking is extremely low (x^2 = 2.188.17 df=12, $p < .001$) the same as in Booking (x^2 = 1.730.75, df = 12, $p < .001$). This leads us to reject the null hypothesis and conclude that there is a relationship of dependency between hotel category and position in the ranking, which is statistically significant.

The construction of the contingency table between hotel category and position in the ranking of both portals is useful to display the results of the chi-square test. The proportional contingency table shows the observed relative values and the Pearson residuals are the difference between the observed and the expected values. We note that depending on hotel category, the hotels do not have the same likelihood of being in the same bracket of the ranking. The 5-star category occupies most positions of the first bracket (between positions 1 and 50), followed by the 4-star category in both Booking and Trip Advisor. However, the hotels that occupy the worst positions (from 300 onwards) are 2-star establishments followed by 1-star ones on Booking.com, and on TripAdvisor 2-star followed by 3-star hotels. In the case of those occupying positions 101-500 of Booking they are 3-star followed by 2-star hotels, however on TripAdvisor they are occupied by 3-star followed by 1-star hotels (see Table 2 and 3).

It is shown that the establishments belonging to 5-star categories are at the top of the rankings, followed by 4-star hotels. Conversely, lower category hotels, with two stars, are located in positions higher than 300 in both rankings, followed by those with one star on Booking and those with three and one stars on TripAdvisor.

To confirm the second hypothesis, H2a: The higher (lower) category of hotel, the higher (lower) the price of the room, Pearson's Chi-squared test was performed between the stars variable and the price variable, as in the previous hypothesis both are ordinal qualitative variables.

The test indicates that the probability that in our sample hotels of any category are in the same brackets of price ranking is extremely low (x^2 = 7216.6, df = 16 p < .001). This tells us that we must reject the null hypothesis and conclude that there is an association between price and hotel category and that it is statistically significant.

The Pearson residuals between price and stars indicate that 1- and 2-star hotels have a lower price and that 4- and 5-star hotels are those that are clearly in the highest price ranking (see Table 4).

In addition, to confirm this aspect a Spearman's rank correlation test was performed, as both are ordinal variables, and a high Spearman's coefficient of correlation is obtained in the set of data of 0.67, with the MEA and ASP regions presenting a higher correlation with coefficients of 0.77 and 0.72, respectively.

To test H2b: The higher (lower) the price of the room, the better (worse) the score, again a Spearman's rank correlation test was performed between price of the room and score on both platforms because the price is an ordinal qualitative variable (from 1 to 5), and the hypothesis is accepted as there is a relationship between the two variables, as can be seen in Table 7 with the complete dataset. With data by regions we note that EUR has the highest correlation both on TripAdvisor and on Booking (0.58 and 0.62, respectively), followed by AME (0.58 and 0.60) and the weakest is in ASP (0.45 in TripAdvisor and 0.50 Booking), as can be seen in Table 8.

Table 8. Correlations between hotel category, rooms, price, scoring and number of reviews, by regions

	Region	Mean	SD	1. [a]	2.	3. [a]	4. [b]	5. [b]	6. [b]	7.
1. Stars	AME	3.45	0.89							
	ASP	3.48	1.00	1						
	EUR	3.38	0.92							
	MEA	3.85	1.00							
2. Rooms	AME	184.10	228.92	0.3593						
	ASP	172.16	196.24	0.5523	1					
	EUR	93.60	110.06	0.4969						
	MEA	189.18	193.31	0.4746						
3. Price	AME	3.39	1.32	0.6693	0.2284 [a]					
	ASP	3.66	1.23	0.7217	0.3786 [a]	1				
	EUR	3.51	1.37	0.6549	0.2576 [a]					
	MEA	3.31	1.44	0.7738	0.3126 [a]					
4. Score TripAdvisor	AME	3.87	0.56	0.4787	0.1006 [b]	0.5772				
	ASP	3.84	0.58	0.4185	0.1295 [b]	0.4549	1			
	EUR	3.85	0.61	0.4320	0.0787 [b]	0.5789				
	MEA	3.87	0.56	0.5338	0.1850 [b]	0.5554				
5. Score Booking	AME	7.98	0.75	0.5035	0.0864 [b]	0.6024	0.8163			
	ASP	7.66	0.93	0.4160	0.1280 [b]	0.5089	0.6905			
	EUR	8.02	0.76	0.4566	0.0817 [b]	0.6256	0.8438	1		
	MEA	7.47	0.98	0.5721	0.1334 [b] (0.00139)	0.5826	0.7946			
6. Reviews TripAdvisor	AME	900.75	1341.74	0.3223	0.6527 [b]	0.3228	0.2147	0.1566		
	ASP	391.55	691.65	0.4353	0.5035 [b]	0.4304	0.2838	0.3239	1	
	EUR	613.47	515.56	0.3910	0.5433 [b]	0.3440	0.2826	0.2692		
	MEA	362.86	504.21	0.4643	0.3824 [b]	0.3894	0.4118	0.4112		

7. Reviews Booking	AME	628.87	855.76	0.0156** (0,547)	0.3623 [b]	-0.1348	-0.0512* (0.048)	-0.0299** (0.248)	0.3858	1
	ASP	388.06	651.67	0.2145	0.4297 [b]	0.1812* (0.02)	0.0698	0.2056	0.6045	
	EUR	889.78	955.66	0.0484	0.4332 [b]	-0.0318	-0.0008** (0.953)	0.0451	0.4269	
	MEA	890.24	1298.94	0.2109	0.6336 [b]	-0.0289** (0.49)	0.1579	0.1918	0.3515	

[a] Spearman rank correlation
[b] Pearson correlation
*All p close to 0 except *p < .05; ** p > .05*

Table 9. Summary of the Hypothesis, methodology and results

Hypothesis	Method	Results
H1 Better hotel category, better score	Spearman's correlation	Confirmed
H1 Better hotel category, better ranking position	Chi square	Confirmed
H2a Better hotel category, more expensive	Chi square Spearman's correlation	Confirmed
H2b More expensive, better score	Spearman's correlation	Confirmed
H2b More expensive, better ranking position	Chi square	Confirmed
H3a Better hotel category, more rooms	Spearman's correlation	Partially confirmed
H3b More rooms, better score	Pearson's correlation	Not confirmed

Also, to test H1: The higher (lower) the price, the better (worse) the position in the ranking, the ranking was divided into four brackets, from position 1 to 50, from 51 to 100, 101 to 300 and 301 to the end.

Based on chi-square analysis we see that the probability that in the sample hotels of any price are in the same brackets of the ranking is extremely low (x^2 = 2943.2, df = 12, p < .001) on TripAdvisor, and (x^2 = 2422, df = 12, p < .001) on Booking. This tells us that we must reject the null hypothesis and conclude that there is an association between price and position in the ranking and that it is statistically significant (see Table 5 and 6).

Depending on price, hotels do not have the same likelihood of being in the same bracket of the ranking. Higher-priced hotels appear in the best positions of the ranking and lower-priced hotels occupy the worst positions, both on Booking and on TripAdvisor.

To test H3a: The higher (lower) the category of the hotel, the higher (lower) the number of rooms, Spearman's rank correlation test was performed between hotel category and number of rooms and the hypothesis is accepted as there is a moderate relationship (0.48) between the two variables. In EUR the correlation is highest (0.55) and in AME the lowest (0.35). Analysing the results by cities, we see that half of the sample shows correlations higher than 0.50 while the other half does not, and so this hypothesis is partially confirmed.

Conversely, the number of rooms is unrelated to the score in either of the two portals, with very low correlations (between 0.06 and 0.1) and so H3b is rejected: The higher (lower) the number of rooms, the better (worse) the score. In this hypothesis we have used the Pearson correlation test because both, number of rooms and score, are quantitative variable.

It is also observed that the highest correlations are those made between the scores of both portals, especially in AME and EUR with correlations of 0.82 and 0.84, respectively. The summary of the Hypothesis, methodology and results, can be seen in Table 9.

5. Discussion

These results confirm the relationship between user satisfaction, measured from the point of view of the score of customer electronic word-of-mouth on TripAdvisor and Booking and hotel classification, confirming the theory of studies that indicates that the overall quality of hotels can be inferred from their stars (Fang et al., 2016) and that the star-rating classification mechanism is the most common customer segmentation pattern in the hotel industry (Dioko et al., 2013) or that an ascending order of accommodation needs is observed when we go from economy to luxury hotels (Zhang, Ye, & Law, 2011) .

The relationship between number of stars and position in the ranking is clear and statistically significant and so the loss of credibility of the star system as a quality standard (Núñez-Serrano et al., 2014) does not correspond to the results obtained with this study where it is possible to relate user satisfaction with the number of stars and manage to reduce the possible adverse effects of information asymmetry (Nicolau & Sellers, 2010).

On the other hand, the price variable analysed in this study confirms that there is a relationship with the score obtained and with hotel category, and so we conclude that higher category hotels have higher prices and that the higher the price, the higher the score awarded by users and hence customers do not evaluate quality independently of price (Fernández-Barcala et al., 2010), thus confirming the theory that the star-rating system is still a stable and consistent predictor of room prices (Israeli, 2002) and, it is traditionally used to rate hotels' quality. It should be stressed that hotels with a better ratio between price and category correspond to the regions ASP and MEA.

Our study confirms the well-established knowledge in services marketing of the positive correlation between price and service expectations (Racherla, Connolly, & Christodoulidou, 2013).

In the light of the results there does not seem to be relationship between price and number of rooms and so, with the present study we cannot conclude that larger hotels requested higher prices, unlike the findings in the study by Israeli, (2002).

As pointed out by Claver-Cortés et al., (2007), size and category are strategic variables together with type of hotel management to increase hotel performance. In our case we can assert that the strategic variables that have a better user score and a better position in the ranking of Booking and TripAdvisor hotels are hotel category and room price.

Finally, the number of rooms is moderately related with hotel category, and it behaves differently depending on the region, being weaker in AME and stronger in EUR, and hence we cannot conclude that this is a common pattern throughout the world.

Conversely, the number of rooms does not confirm a better user score, and hence hotel size does not affect user satisfaction. Where there is a high and statistically significant correlation is between the number of rooms and the number of reviews on TripAdvisor and Booking, which leads us to assert that the logic that one could expect of the greater the number of rooms, the more customers and therefore the more reviews, is confirmed in this study.

However, this behaviour is not observed in the same way in all regions: in AME there is a greater relationship between number of reviews on TripAdvisor and number of rooms and in MEA for the Booking portal.

However, the highest correlations are seen to be those which take place between the scores of both portals, this being indicative that the users of both platforms have very similar opinions about the same hotels.

6. Conclusions

The differences in criteria in the allocation of hotel category in each country and even within the same country, in each administrative region, do not seem to prevent the existence of a relationship between stars and the satisfaction of hotel guests measured from the point of view of the score awarded with the opinions of previous customers on the TripAdvisor and Booking portals since a higher hotel category presents a better score by customers who give their opinion on one of the two portals studied and, therefore, the hotels obtain a better position in the ranking of each website.

The eWOM of consumers from the demand side corroborates the validity of the classification system offered by a third party and each additional star corresponding to the hotel category presents a higher level of user satisfaction, measured by the assessment awarded in each one on both portals, placing the establishment in a better position in each ranking.

On the other hand, this study confirms the theory that the higher the hotel category the higher the price set by the hotel, and it contributes to the existing literature on hotel prices analysing them not from the point of view of monetary units, but in the form of a ranking (from 1 to 5) provided by Booking and concluding that the hotels with higher prices achieve a better score from customers and therefore a better position in the ranking of each portal.

In a market characterized by asymmetric information, attributes established by different actors are seen to have joined, such as hotel category which is determined by a third party, price, which is fixed by the supply side, and score, awarded by past guests, i.e. by the demand side, and all of these items, from different perspectives, contribute to reduce the adverse effects of asymmetric information in the hotel industry. So, the results show that hotel classification system fulfils its purpose, as both prices and customers' scores increase with each additional star.

This finding has implications for private managers, who should be aware of how the stars of their establishments are announced not only in information that they themselves control from their establishment (websites, blogs, their profiles on social networks, advertising, etc.) but also the star-rating system assigned by the different third-party electronic distribution channels that in some cases provide differences with the reality (Denizci Guillet & Law, 2010; Leung et al., 2011).

Moreover, as has been shown, the overall quality of hotels can be inferred from their stars (Fang et al., 2016), customers can use the stars as a tool in the choice of hotel establishment and the price they are willing to pay, both coinciding with the feedback provided by previous customers.

Finally, the main contribution of this work is that the conclusions are obtained through the analysis of a large amount of data, more than 14,000 hotels in 100 cities throughout the world, providing a global vision whereas to date similar studies had only been conducted in certain cities or at most in an entire country. In addition, the effort of comparing two of the major portals of opinion in the hospitality industry as are TripAdvisor and Booking is noteworthy and that the data offer certain similarities of behaviour.

The limitations of this study lie in the inconsistency between the star-rating system assigned by the different third-party electronic distribution channels and the one actually assigned, as confirmed by Denizci Guillet & Law, 2010; Leung et al., (2011). In our study we take into consideration the star-rating system of Booking which is a very well-known OTA in the hospitality industry, but the results could be slightly different if we took into account the star-rating system assigned by other channels. Empirical replications using other channels to get the star rating may provide more insights to this discussion.

Acknowledgements

This work has been partially funded by Ministerio de Economía y Competitividad research project TIN2015-71799-C2-2-P.

7. References

Abrate, G., Capriello, A., & Fraquelli, G. (2011). When quality signals talk: Evidence from the Turin hotel industry. *Tourism Management*, *32*(4), 912–921. doi:10.1016/j.tourman.2010.08.006

Abrate, G., & Viglia, G. (2016). Strategic and tactical price decisions in hotel revenue management. *Tourism Management*, *55*, 123–132. doi:10.1016/j.tourman.2016.02.006

Akerlof, G. A. (1970). The Market for" Lemons": Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics*, *84*(3), 488–500.

Anderson, C. K. (2012). The Impact of Social Media on Lodging Performance. *Cornell Hospitality Report*, *12*(15), 4–11. Retrieved from http://www.budigitalhub.com/sites/default/files/white_papers/HotelsSocialMedia.pdf

Banerjee, S., & Chua, A. Y. K. (2016). In search of patterns among travellers' hotel ratings in TripAdvisor. *Tourism Management*, *53*, 125–131. doi:10.1016/j.tourman.2015.09.020

Baum, J. A. C., & Mezias, S. J. (1992). Localized competition and organizational failure in the Manhattan hotel industry, 1898-1990. *Administrative Science Quarterly*, 580–604.

Ben Aissa, S., & Goaied, M. (2016). Determinants of Tunisian hotel profitability: The role of managerial efficiency. *Tourism Management*, *52*, 478–487. doi:10.1016/j.tourman.2015.07.015

Booking.com. (2016). Retrieved April 23, 2016, from http://www.booking.com/content/about.en-gb.html

Bulchand-Gidumal, J., Melián-González, S., & González López-Valcárcel, B. (2011). Improving hotel ratings by offering free Wi-Fi. *Journal of Hospitality and Tourism Technology*, *2*(3), 235–245. doi:10.1108/17579881111173776

Butler, R. W. (1980). The concept of a tourist area cycle of evolution: Implications for management of resources. *The Canadian Geographer/Le Géographe Canadien*, *24*(1), 5–12. doi:10.1111/j.1541-0064.1980.tb00970.x

Cantallops, A. S., & Salvi, F. (2014). New consumer behavior: A review of research on eWOM and hotels. *International Journal of Hospitality Management*, *36*, 41–51.

Cezar, A., & Ögüt, H. (2016). Analyzing conversion rates in online hotel booking. *International Journal of Contemporary Hospitality Management*, *28*(2), 286–304. doi:10.1108/IJCHM-05-2014-0249

Chen, C.-F., & Rothschild, R. (2010). An application of hedonic pricing analysis to the case of hotel rooms in Taipei. *Tourism Economics*, *16*(3), 685–694.

Chung, W., & Kalnins, A. (2001). Agglomeration effects and performance: A test of the Texas lodging industry. *Strategic Management Journal*, *22*(10), 969–988.

Claver-Cortés, E., Molina-Azorín, J. F., & Pereira-Moliner, J. (2007). The impact of strategic behaviours on hotel performance. *International Journal of Contemporary Hospitality Management*, *19*(1), 6–20. doi:10.1108/09596110710724125

Clerides, S., Nearchou, P., & Pashardes, P. (2005). Intermediaries as bundlers, traders and quality assessors: the case of UK tour operators.

Cohen, E. (1972). Toward a sociology of international tourism. *Social Research*, 164–182.

Danziger, S., Israeli, A., & Bekerman, M. (2006). The relative role of strategic assets in determining customer perceptions of hotel room price. *International Journal of Hospitality Management*, *25*(1), 129–145. doi:10.1016/j.ijhm.2004.12.005

de Oliveira Santos, G. E. (2016). Worldwide hedonic prices of subjective characteristics of hostels. *Tourism Management*, *52*, 451–454. doi:10.1016/j.tourman.2015.07.001

Dellarocas, C. (2003). The digitization of word of mouth: Promise and challenges of online feedback mechanisms. *Management Science*, *49*(10), 1407–1424.

Dellarocas, C., Zhang, X. (Michael), & Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing*, *21*(4), 23–45. doi:10.1002/dir.20087

Denizci Guillet, B., & Law, R. (2010). Analyzing hotel star ratings on third-party distribution websites. *International Journal of Contemporary Hospitality Management*, *22*(6), 797–813. doi:10.1108/09596111011063098

Dioko, L. A. N., So, S.-I. (Amy), & Harrill, R. (2013). Hotel category switching behavior—Evidence of mobility, stasis or loyalty. *International Journal of Hospitality Management*, *34*, 234–244. doi:10.1016/j.ijhm.2013.04.002

Espinet, J. M., Saez, M., Coenders, G., & Fluvià, M. (2003). Effect on prices of the attributes of holiday hotels: a hedonic prices approach. *Tourism Economics*, *9*(2), 165–177. doi:10.5367/000000003101298330

Fang, B., Ye, Q., Kucukusta, D., & Law, R. (2016). Analysis of the perceived value of online tourism reviews: Influence of readability and reviewer characteristics. *Tourism Management*, *52*, 498–506. doi:10.1016/j.tourman.2015.07.018

Fernández-Barcala, M., González-Díaz, M., & Prieto-Rodríguez, J. (2010). Hotel quality appraisal on the Internet: a market for lemons? *Tourism Economics*, *16*(2), 345–360. doi:10.5367/000000010791305635

Geerts, W. (2016). *Top 100 City Destinations Ranking*. Retrieved from http://blog.euromonitor.com/2016/01/top-100-city-destinations-ranking-2016.html

Godes, D., & Mayzlin, D. (2004). Using Online Conversations to Study Word-of-Mouth Communication. *Marketing Science*, *23*(4), 545–560. doi:10.1287/mksc.1040.0071

Gretzel, U., & Yoo, K. H. (2008). Use and Impact of Online Travel Reviews. In P. O'Connor, W. Höpken, & U. Gretzel (Eds.), *Information and Communication Technologies in Tourism* (pp. 35–46). Vienna: Springer Vienna. doi:10.1007/978-3-211-77280-5_4

Hamilton, J. M. (2007). Coastal landscape and the hedonic price of accommodation. *Ecological Economics*, *62*(3), 594–602.

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? *Journal of Interactive Marketing*, *18*(1), 38–52. doi:10.1002/dir.10073

Hong, T. (2006). The influence of structural and message features on Web site credibility. *Journal of the American Society for Information Science and Technology*, *57*(1), 114–127. doi:10.1002/asi.20258

Hu, N., Bose, I., Gao, Y., & Liu, L. (2011). Manipulation in digital word-of-mouth: A reality check for book reviews. *Decision Support Systems*, *50*(3), 627–635. doi:10.1016/j.dss.2010.08.013

Ingram, P. (1996). Organizational form as a solution to the problem of credible commitment: The evolution of naming strategies among US hotel chains, 1896–1980. *Strategic Management Journal*, *17*(S1), 85–98.

Israeli, A. A. (2002). Star rating and corporate affiliation: their influence on room price and performance of hotels in Israel. *International Journal of Hospitality Management*, *21*(4), 405–424. doi:10.1016/S0278-4319(02)00037-3

Jeacle, I., & Carter, C. (2011). In TripAdvisor we trust: Rankings, calculative regimes and abstract systems. *Accounting, Organizations and Society*, *36*(4-5), 293–309. doi:10.1016/j.aos.2011.04.002

Karakaya, F., & Barnes, N. G. (2010). Impact of online reviews of customer care experience on brand or company selection. *Journal of Consumer Marketing*, *27*(5), 447–457. doi:10.1108/07363761011063349

Lant, T. K., & Baum, J. A. C. (1995). Cognitive sources of socially constructed competitive groups: Examples from the Manhattan hotel industry. *The Institutional Construction of Organizations*, *15*, 38.

Lee, J., Park, D.-H., & Han, I. (2008). The effect of negative online consumer reviews on product attitude: An information processing view. *Electronic Commerce Research and Applications*, *7*(3), 341–352. doi:10.1016/j.elerap.2007.05.004

Leung, D., Lee, H. A., & Law, R. (2011). The Impact of Culture on Hotel Ratings: Analysis of Star-Rated Hotels in China. *Journal of China Tourism Research*, *7*(3), 243–262. doi:10.1080/19388160.2011.599239

Litvin, S. W., Goldsmith, R. E., & Pan, B. (2008). Electronic word-of-mouth in hospitality and tourism management. *Tourism Management*, *29*(3), 458–468. doi:10.1016/j.tourman.2007.05.011

Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing*, *70*(3), 74–89.

López Fernández, M. C., & Serrano Bedia, A. M. (2004). Is the hotel classification system a good indicator of hotel quality? *Tourism Management*, *25*(6), 771–775. doi:10.1016/j.tourman.2004.06.007

Masiero, L., Nicolau, J. L., & Law, R. (2015). A demand-driven analysis of tourist accommodation price: A quantile regression of room bookings. *International Journal of Hospitality Management*, *50*, 1–8.

Monty, B., & Skidmore, M. (2003). Hedonic Pricing and Willingness to Pay for Bed and Breakfast Amenities in Southeast Wisconsin. *Journal of Travel Research*, *42*(2), 195–199. doi:10.1177/0047287503257500

Nicolau, J. L., & Sellers, R. (2010). The quality of quality awards: Diminishing information asymmetries in a hotel chain. *Journal of Business Research*, *63*(8), 832–839. doi:10.1016/j.jbusres.2009.06.009

Núñez-Serrano, J. A., Turrión, J., & Velázquez, F. J. (2014). Are stars a good indicator of hotel quality? Assymetric information and regulatory heterogeneity in Spain. *Tourism Management*, *42*, 77–87. doi:10.1016/j.tourman.2013.10.004

Öğüt, H., & Onur Taş, B. K. (2012). The influence of internet customer reviews on the online sales and prices in hotel industry. *The Service Industries Journal*, *32*(2), 197–214. doi:10.1080/02642069.2010.529436

Park, D.-H., Lee, J., & Han, I. (2007). The Effect of On-Line Consumer Reviews on Consumer Purchasing Intention: The Moderating Role of Involvement. *International Journal of Electronic Commerce*, *11*(4), 125–148. doi:10.2753/JEC1086-4415110405

Petz, G., & Greiner, A. (2014). First in Search–How to Optimize Search Results in E-Commerce Web Shops. In *HCI in Business* (pp. 566–574). Springer.

Racherla, P., Connolly, D. J., & Christodoulidou, N. (2013). What Determines Consumers' Ratings of Service Providers? An Exploratory Study of Online Traveler Reviews. *Journal of Hospitality Marketing & Management*, <(2), 135–161. doi:10.1080/19368623.2011.645187

Ratcliff, J. W., & Metzener, D. E. (1988). Pattern-matching-the gestalt approach. *Dr Dobbs Journal*, *13*(7), 46.

Saló, A., Garriga, A., Rigall-I-Torrent, R., Vila, M., & Fluvià, M. (2014). Do implicit prices for hotels and second homes show differences in tourists' valuation for public attributes for each type of accommodation facility? *International Journal of Hospitality Management*, *36*, 120–129. doi:10.1016/j.ijhm.2013.08.011

Sparks, B. A., & Browning, V. (2011). The impact of online reviews on hotel booking intentions and perception of trust. *Tourism Management*, *32*(6), 1310–1323.

Steffes, E. M., & Burgee, L. E. (2013). Social ties and online word of mouth. Retrieved from http://www.emeraldinsight.com/doi/abs/10.1108/10662240910927812#.VFZYq3xBx7s.mendeley

Torres, E. N., Adler, H., & Behnke, C. (2014). Stars, diamonds, and other shiny things: The use of expert and consumer feedback in the hotel industry. *Journal of Hospitality and Tourism Management*, *21*, 34–43. doi:10.1016/j.jhtm.2014.04.001

TripAdvisor. (2016). Retrieved April 1, 2016, from https://www.tripadvisor.com/PressCenter-c6-About_Us.html

Vermeulen, I. E., & Seegers, D. (2009). Tried and tested: The impact of online hotel reviews on consumer consideration. *Tourism Management*, *30*(1), 123–127. doi:10.1016/j.tourman.2008.04.008

Viglia, G., Furlan, R., & Ladrón-de-Guevara, A. (2014). Please, talk about it! When hotel popularity boosts preferences. *International Journal of Hospitality Management*, *42*, 155–164. doi:10.1016/j.ijhm.2014.07.001

Xie, K. L., Zhang, Z., & Zhang, Z. (2014). The business value of online consumer reviews and management response to hotel performance. *International Journal of Hospitality Management*, *43*, 1–12. doi:10.1016/j.ijhm.2014.07.007

Ye, Q., Law, R., Gu, B., & Chen, W. (2011). The influence of user-generated content on traveler behavior: An empirical investigation on the effects of e-word-of-mouth to hotel online bookings. *Computers in Human Behavior*, *27*(2), 634–639.

doi:10.1016/j.chb.2010.04.014

Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1993). The nature and determinants of customer expectations of service. *Journal of the Academy of Marketing Science*, *21*(1), 1–12.

Zhan-Qing, L., & Liu, J. C. (1993). Assessment of the hotel rating system in China. *Tourism Management*, *14*(6), 440–452.

Zhang, Z., Ye, Q., & Law, R. (2011). Determinants of hotel room price. *International Journal of Contemporary Hospitality Management*, *23*(7), 972–981. doi:10.1108/09596111111167551

Zhang, Z., Zhang, Z., Wang, F., Law, R., & Li, D. (2013). Factors influencing the effectiveness of online group buying in the restaurant industry. *International Journal of Hospitality Management*, *35*, 237–245. doi:10.1016/j.ijhm.2013.06.012

Zhu, F., & Zhang, X. (2010). Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of Marketing*, *74*(2), 133–148.

Zong, J., Tang, F., Huang, W., & Ma, J. (2010). Online Pricing Dispersion of Chinese Hotels. *Journal of China Tourism Research 4*(3-4), 248-260. Retrieved from http://www.tandfonline.com/doi/abs/10.1080/19388160802502447#.VqeHnys0L9E.mendeley

7. Are users' ratings on TripAdvisor similar to hotel categories in Europe?

Pages 100 to 112 contain this article:

Martin-Fuentes, E., Mateu, C., & Fernandez, C. (2018). Are users' ratings on TripAdvisor similar to hotel categories in Europe? *Cuadernos de Turismo.* (Accepted 22 January 2018).

Journal Metrics
Scopus
SCImago Journal Rank (SJR): 0.194
Year 2017 Fourth Quartile. Subject area: Tourism, Leisure and Hospitality Management. Rank 77 of 101
Year 2017 Third Quartile. Subject area: Geography, Planning and Development. Rank 440 of 699
Master Journal List of Thomson Reuters and Web of Science (WOS)

UNIVERSIDAD DE
MURCIA

CIF Q3018001B

Murcia, 22 de enero de 2018

Cayetano Espejo Marín, Director de la revista **Cuadernos de Turismo (ISSN 1139-7861)**, editada por la Universidad de Murcia desde 1998, certifica que se encuentra aceptado para su publicación en el número 42, correspondiente al segundo semestre de 2018, el artículo "Are users' ratings on TripAdvisor similar to hotel categories in Europe?", del que son autores Eva Martín Fuentes, Carles Mateu y César Fernández.

En 2012 la Fundación Española para la Ciencia y la Tecnología (FECYT) califica Cuadernos de Turismo como revista Excelente, sello de Calidad que renueva en 2015.

En 2014 la revista es incluida en Scopus, y valorada por Scimago Journal & Country Rank. Desde 2015 está presente en la base de datos Emerging Source Citation Index (ESCI) de Thomson Reuters.

UNIVERSIDAD DE MURCIA
DEPARTAMENTO DE GEOGRAFÍA
FACULTAD DE LETRAS

Cayetano Espejo Marín

Facultad de Letras
Departamento de Geografía
Campus Universitario La Merced. 30001 Murcia
T. 868 88 30 00 – F. 868 88 31 24 – **www.um.es/dp-geografia**

7.1. Introduction

Hotel classification systems are often questioned because they use criteria that could be obsolete, for example, some regulations require hotels to have a public telephone line in the common areas but the norms do not say anything about the need to have Wi-Fi or high-speed internet.

Moreover, the regulatory criteria for allocating a given category to a given hotel are not consistent between regions and countries, and there are no unified criteria for assigning stars worldwide. However, a process of regulatory harmonization is being carried out in Europe by the Hotrec Association (Hotels, Restaurants & Cafes in Europe) (Hotrec, 2015).

There is also a lack of reciprocation between hotel category and services offered, according to the guests expectations (Minazzi, 2010), and hotel classification systems have lost credibility as a quality standard (Núñez-Serrano, Turrión, & Velázquez, 2014).

Although hotel categories have received some criticism, as mentioned previously, some studies have indeed confirmed that hotel quality can be inferred from their stars (Fang et al., 2016) and that hotel categories serve to segment customers (Dioko et al. 2013).

The aim of this study is to determine whether the hotel category of 78,363 hotels in nine European countries is related to customer satisfaction, measured from the point of view of the user ratings on TripAdvisor.

7.2. Contribution to the state-of-the-art

The most important finding is that higher category hotels have higher ratings awarded by users on TripAdvisor in nine European countries with the exception of 1-star and 2-star hotels in most of the countries analyzed (7 out 9), and 1-star and 3-star hotels in four of the countries analyzed. In these instances, there are similarities in the users' average scores, a fact indicating that customers do not perceive significant differences between these hotel categories.

Differences in criteria in the allocation of hotel categories in European countries, which may even differ from one region to the next within the same country, do not present a problem, as there is a relationship between the category of a hotel and user ratings.

This finding could help the industry to obtain a closer fit between classification systems and online reviews by including UGC in future classification systems to be consistent with customer needs (Blomberg-Nygard & Anderson 2016).

This study yields a managerial implication because, after downloading data for all the hotels of 9 European countries, it was found that more than 20,000 hotels did not have the category that had been assigned to them on TripAdvisor. In this respect, hoteliers are advised to take care of the information provided, not only on websites, blogs, ads or social media accounts controlled by them, but also by the different online distribution channels and other COPs, such as TripAdvisor.

7.3. Journal paper

Are users' ratings on TripAdvisor similar to hotel categories in Europe?

Abstract

European countries do not have the same hotel classification system. Therefore, the criteria and requirements used to assign star ratings to hotels do not concur among the different countries.

There have been some criticisms about the way hotel stars are assigned, because the requirements do not necessarily match the quality of service offered. Technical criteria such as infrastructure and room dimensions are taken into account, but users do not perceive them although these have nothing to do with the satisfaction.

This study aims to determine whether the hotel category of about 80,000 hotels in 9 different European countries on TripAdvisor is related to customer satisfaction, measured from the point of view of the user ratings on this site.

The one-way ANOVA test shows that there are significant differences between the average ratings of the hotel category, except in the classification of 1-star and 2-star hotels from most countries analysed that behave similarly, and 1-star and 3-star hotels from Austria, Greece, Portugal, Spain and UK that are ranked similarly.

Keywords: star-rate system, eWOM, User-Generated Content, hotels, TripAdvisor, Big data

¿Se parecen las puntuaciones de los usuarios en TripAdvisor con las categorías hoteleras en Europa?

Resumen

Los hoteles de Europa no siguen el mismo sistema de clasificación hotelera, por lo que los criterios y los requerimientos usados para asignar las estrellas no coinciden entre países, e incluso ni entre regiones de un mismo país.

Hay algunas críticas sobre la forma de asignar las estrellas hoteleras porque los requisitos establecidos no coinciden necesariamente con la calidad del servicio ofrecido.

Por eso, este estudio determina si la categoría hotelera de más de 80.000 hoteles en 9 países europeos está relacionada con la satisfacción de los clientes, medida a través de las puntuaciones otorgadas en TripAdvisor.

A través de un contraste ANOVA se demuestra que hay diferencias significativas entre las puntuaciones medias de cada categoría hotelera, excepto en las categorías de 1 y 2 estrellas en la mayoría de países analizados que se comportan de forma similar, y entre 1 y 3 estrellas de Austria, Grecia, Portugal, España y Reino Unido que también se comportan de manera parecida.

Palabras clave: clasificación hotelera, boca-oreja digital, contenido generado por los usuarios, hotels, TripAdvisor, Big data

1. Introduction

Hotel classification systems do not follow the same pattern throughout the world because each country has its own criteria, while the European level attempts to launch a process of harmonisation of different regulations by the Hotrec Association (Hotels, Restaurants & Cafes in Europe) to implement a scoring system that allows unity among criteria for allocation of stars in different countries (Hotrec, 2015).

This process is not an easy task, because even within the same countries, there are different systems, for example, Spain has 17 different classifications, as many as some autonomous governments, which have the power to regulate this ranking. In fact, the Hotrec has been working on the harmonization process since 2004 and only 16 European countries are members of the HotelStars Union (HotelStars Union, 2017).

Hotel classifications have been questioned in some studies, not only because countries do not follow the same criteria, but because the hotel classification systems have lost credibility as a quality standard (Núñez-Serrano et al., 2014) because some of the criteria are outdated (Torres et al., 2014) or because the customer expectations are related to the quality of services more than to the hotel classifications (López Fernández & Serrano Bedia, 2004).

Otherwise, although the star-rating classification systems are different all over the world, it has been proven that there is a relationship between star-rating classification and satisfaction measured from the point of view of scores assigned by users on advice websites such as TripAdvisor and on sales websites such as Booking.com (Martin-Fuentes, 2016).

A study conducted by the World Tourism Organization of the United Nations (UNWTO) considers the idea to merge the official hotel classifications with the online guest reviews in order to implement an integrative system (Blomberg-Nygard & Anderson, 2016) that allows consumers to combine the search of information through the online reviews filtered by hotel categories.

Online travel reviews are an important information source for travelers before taking the decision to book a hotel (Cezar & Ögüt, 2016) and TripAdvisor is one of the most visited online travel-related website worldwide, gaining importance daily both in the number of users and reviews about destinations, hotels, restaurants, things to do, and since 2016 about airline companies.

The aim of this research is to confirm whether the hotel star-rated classification system matches the user satisfaction measured from the point of view of the ratings obtained from users on TripAdvisor.

Hotel category and customer ratings of a total of 80,000 hotels in 9 different European countries on TripAdvisor were downloaded automatically. The singularity of this study is that the results were obtained from a large volume of data and that contributes to the scarce literature about hotel classification systems.

A review of the literature from word of mouth and hotel classification systems follows this introduction. Next the methodology used for analysing the data, the results and a discussion will be presented. Finally the main conclusions of this study will be described.

2. Literature review

2.1 Word of mouth

The word of mouth (WOM) phenomenon has been studied widely in the marketing field (Arndt, 1967) and it refers to the customers' communications about their experiences (E. W. Anderson, 1998).

WOM through Web 2.0 is known as electronic word of mouth (eWOM) (Hennig-Thurau et al., 2004) and is defined as "all informal communications directed at consumers through Internet-based technology related to the usage or characteristics of particular goods and services, or their sellers" (Litvin et al. 2008: 461). The eWOM has also captured the attention of recent research-related tourist services (Guo, Barnes, & Jia, 2017; Martin-Fuentes, Mateu, & Fernandez, 2018; Raguseo & Vitari, 2017; Xiang et al., 2017).

Both, the traditional WOM and eWOM, have been studied concluding that the use of social media before travelling is widely exteded (Martin-Fuentes, Daries-Ramon, & Mariné-Roig, 2015). Online travel reviews have increased exponentially and there is usually a huge number of reviews available for the same product or service (De Ascaniis & Gretzel, 2012).

TripAdvisor is the world's largest travel site with more than 500 million reviews and a community of 415 million average unique monthly visitors (TripAdvisor, 2017).

TripAdvisor is one of the most influential eWOM sources in the hospitality and tourism context (Yen & Tang, 2015) not only does it supply a source of information for travellers, but also its data allows researchers to obtain useful information focusing on User-Generated Content (UGC) through the online travel reviews posted by consumers (Ayeh et al., 2013; Balagué et al., 2016; B. Liu et al., 2015; Melián-González, Bulchand-Gidumal, & González López-Valcárcel, 2013) and has been the most frequently studied platform in the last five years (Chen & Law, 2016).

It can be emphasised that the percentage of consumers who consult TripAdvisor before booking a room in a hotel is increasing (Anderson 2012) and that the consumers' reviews are more credible if they are published in popular online communities of travellers such as TripAdvisor (Casalo et al., 2015).

2.2 Hotel classification systems

Literature on hotel classification systems is rather scarce, finding some studies concerning the regulations applied by the countries (Arcarons i Simon, Goitia Serra, & González Aznar, 2008; Minazzi, 2010; Talias, 2016) and some works about the relationship between quality and hotel classification mechanism (Abrate, Capriello, & Fraquelli, 2011; López Fernández & Serrano Bedia, 2004; Núñez-Serrano et al., 2014; Torres et al., 2014).

Hotel star-rating classification systems throughout the world are established from various standards set by national or autonomous governments or by independent organizations. This system is universally recognized, and the most common method for classifying hotels is using from 1 to 5 stars, although the requirements to assign the stars differ, depending on the institution that assigns them.

Other symbols such as diamonds awarded by the American Automobile Association (AAA), crowns assigned by the National Tourist Boards in the United Kingdom (NTBs) or suns (Narangajavana & Hu, 2008) are used to classify hotels.

There is no common standard concerning what a hotel from each category should provide; rather, obtaining the stars is based on objective criteria, such as infrastructure, services, amenities and the sizes of the rooms or the common spaces.

The star-rating classification mechanism is the most common customer segmentation pattern in the hotel industry (Dioko et al., 2013). The highest hotel categories can be considered as an indicator of high quality (Abrate et al., 2011); it can also be assumed that there is a relationship between the hotel category, the room price and guest satisfaction (Martin-Fuentes, 2016).

Often the hotel category is a method used by consumers to select a hotel (Núñez-Serrano et al., 2014). Furthermore, the hotel quality can be inferred from their stars (Fang et al., 2016).

Not all scholarly research confirms the relationship between the star-rating classification system and quality. Callan (1995) concluded that customers did not perceive the grades of any hotel rating system as a strongly important indicator in the selection of a hotel. Additionally, López Fernández & Serrano Bedia (2004) found significant differences among expectations, perceptions and hotel categories. Sometimes there is a lack of correspondence between the hotel ranking and the service offered, based on customer expectations (Minazzi, 2010).

A study of the United Nations World Tourism Organization confirms that consumers and hoteliers support the idea of closer integration of hotel classifications and guest reviews proposing a modification to existing classifications systems which includes guest review data (Blomberg-Nygard & Anderson 2016).

On TripAdvisor, hotel categories are shown by stars in the description. The system used to assign the stars on TripAdvisor is provided by a third party depending on the country. The United Kingdom gets the category information from the AA, England from VisitEngland and all other European countries from Expedia or Giata (TripAdvisor, 2014).

Guest satisfaction measured from the point of view of the users' ratings has been studied by multiple authors recently (Kim & Park, 2017; Martin-Fuentes, Fernandez, Mateu, & Marine-Roig, 2018; Pacheco, 2017; Tussyadiah & Zach, 2017), and although it is not measured in the traditional way the association of the UGC with the guest experience is strong (Xiang et al., 2015).

3. Research aim and methodology

According to the existing literature about hotel classification systems and the effects of the ratings posted on TripAdvisor, the aim of this study is to determine whether the hotel star-rated classification system matches the user satisfaction measured by the ratings obtained from past users' scores on TripAdvisor.

We automatically gathered the data from TripAdvisor, taking into account only "hotels," discarding other options. The process took 13 hours and a total of 82,591 hotels on TripAdvisor were downloaded from 9 European countries classified by TripAdvisor as some of the most popular destinations: Austria, Germany, France, Greece, Italy, Poland, Portugal, Spain and the United Kingdom.

The data were collected on August 2016 using an automatically controlled web browser that simulated user navigation (clicks and selections) for TripAdvisor developed in Python.

Some values were missing from our dataset because some properties had not received any ratings by users. After omitting the missing values the dataset consisted of 78,363 hotels and 15,752,196 reviews on TripAdvisor, as shown in Table 1.

Table 1. Sample data by countries

Country	Hotels	Mean rating	Standard deviation rating	Total reviews	Mean reviews	Standard deviation reviews
Austria	3,527	4.13	.64	371,580	105.35	208.43
Germany	9,372	3.83	.67	1,020,866	108.93	257.02
France	16,647	3.71	.71	2,603,677	156.41	249.67
Greece	6,257	4.02	.71	985,009	157.43	274.05
Italy	19,642	3.99	.63	3,447,834	175.53	249.86
Poland	2,415	3.87	.70	210,834	87.30	213.44
Portugal	1,902	3.92	.64	517,165	271.91	423.36
Spain	10,424	3.83	.67	3,041,784	291.81	504.23
UK	8,177	3.95	.64	3,553,447	434.57	540.06
Total	78,363	3.89	.68	15,752,196	201.02	352.44

The data collected were transferred to a CSV file, which allows analysis of the information. The statistical calculations were performed using SPSS software, version 20.

The one-way ANOVA test was performed to determine whether there were any significant differences between the mean score of the five hotel categories. It tested the null hypothesis:

H_0: $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ being μ the mean score by hotel category

H_A: There are at least two group means that are significantly different from each other.

TripAdvisor ranks hotels with stars from 1 to 5 also assigning hotel categories to the midpoints to match all the general categories from one to five stars. In this study the midpoints of each category were assigned to the previous category, so 1.5-star hotels were assigned together with the 1-star hotels; 2.5 to 2-star hotels and so on. A total of 20,202 hotels with non-defined stars were excluded from this part of the study.

4. Results

The best hotels rated on average were those from Austria and Greece and the worst were from France, Germany and Spain, as shown in Table 1.

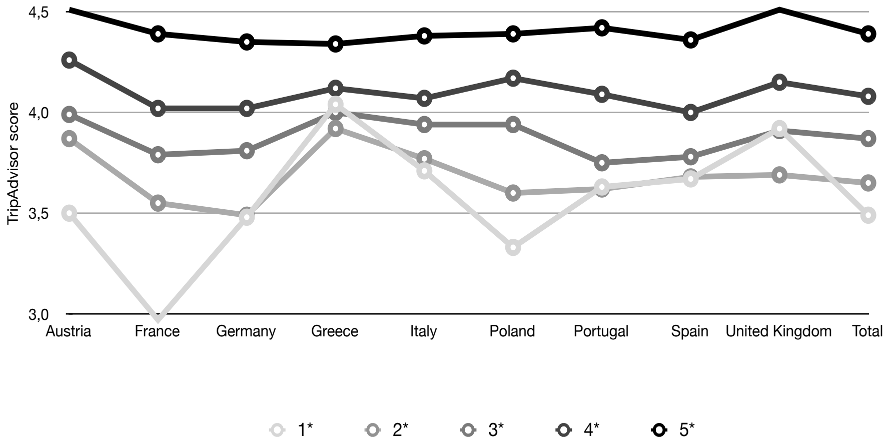
As seen in Table 2 and in Figure 1, on TripAdvisor 1-star hotels from France were the worst rated on average and those from Greece the best; 2-star hotels from Germany were the worst rated and again Greece had the best rated; 3-star hotels from Portugal were the worst and the best were in Greece; 4-star hotels from Spain were the worst on average and those from Austria were ranked the best; and 5-star hotels from Greece were the worst and the best were in Austria and the United Kingdom.

Table 2. Hotel rating by countries and by hotel categories

Star	Austria		France		Germany		Greece		Italy	
	N	M	N	M	N	M	N	M	N	M
1	9	3.50	549	2.97	120	3.48	152	4.04	255	3.71
2	77	3.87	3,559	3.55	785	3.49	1,195	3.92	801	3.77
3	1,121	3.99	5,556	3.79	4,516	3.81	1,672	4.00	7,336	3.94
4	1,566	4.26	1,949	4.02	2,005	4.02	1,026	4.12	4,835	4.07
5	87	4.51	296	4.39	169	4.35	387	4.34	382	4.38

Star	Poland		Portugal		Spain		UK		Total	
	N	M	N	M	N	M	N	M	N	M
1	27	3.33	12	3.63	521	3.67	131	3.92	1,776	3.49
2	175	3.60	161	3.62	1,562	3.68	736	3.69	9,051	3.65
3	938	3.94	593	3.75	3,292	3.78	3,573	3.91	28,597	3.87
4	356	4.17	620	4.09	2,680	4.00	1,680	4.15	16,717	4.08
5	61	4.39	144	4.42	329	4.36	159	4.51	2,014	4.39

Fig. 1. Mean score by countries and by hotel categories



To assess the equality of variances or homoscedasticity, Levene's test was performed and the assumption of homogeneity was not met, because ($F(4, 58150) = 559.2$, $p < .001$). Since the assumption of homogeneity of variance was not met for this data, we used the obtained Welch's adjusted F ratio ($F(4, 7318.5) = 1675.5$, $p < .001$). We can conclude that at least two of the five hotel categories differ significantly in their average scores.

Beyond that, post hoc follow-up was performed, since there were unbalanced groups because the number of hotels in each category was different and since the homogeneity of variance assumption was not met, we use the statistical Games-Howell to test the differences between all unique pairwise comparisons. The results concluded that there was a significant effect of mean score awarded by past users on TripAdvisor for all the five hotel categories ($p < .001$).

By countries, Levene's test showed that the assumption of homogeneity was not met in any country ($p < .001$) and in the Welch's adjusted F ratio ($p < .001$). As the data did not meet the homogeneity of variances assumption, we again ran the Games Howell post hoc test to determine which pairs of the five hotel categories differed significantly. The results of the p-value are shown in Table 3.

Table 3. Games Howell post hoc test (p-value)

Country	1-2 stars 2-1 stars	1-3 stars 3-1 stars	1-4 stars 4-1 stars	2-3 stars 3-2 stars	Other categories
Austria	p = .484	p = .213	p < .05	p = .646	p < .05
France	p < .001	p < .001	p < .001	p < .001	p < .001
Germany	p = 1	p < .001	p < .001	p < .001	p < .001
Greece	p = .307	p = .960	p = .640	p < .05	p < .001
Italy	p = .793	p < .001	p < .001	p < .001	p < .001
Poland	p = .285	p < .001	p < .001	p < .001	p < .001
Portugal	p = 1	p = .931	p = .069	p = .092	p < .05
Spain	p = .999	p < .05	p < .001	p < .001	p < .001
UK	p < .001	p = .999	p < .001	p < .001	p < .001

The results revealed that there were significant differences among most of the categories, except in hotels of 1 and 2 stars from seven countries and except in hotels of 1 and 3 stars from four countries.

1-star and 4-star hotels were not significantly different in Greece and Portugal, as well as 2-star and 3-star hotels in Austria and Portugal.

5. Discussion

The mean differences are statistically significant among all categories except the 1-star with 2-star hotels in Austria, Germany, Greece, Italy, Poland, Portugal and Spain; 1-star with 3-star hotels in Austria, Greece, Portugal and United Kingdom; 1-star with 4-star hotels in Greece and Portugal and 2-star with 3-star hotels in Austria and Portugal, which did not show any significantly different mean scores on TripAdvisor.

In most of the countries analysed, there was no mean difference of TripAdvisor scores between 1-star and 2-star hotels. The exception were hotels from France and from the United Kingdom, but as can be observed in Table 2, in the United Kingdom 1-star ratings are better rated by users than those of 2-star hotels.

The 1-star hotels are the ones that have the most different mean score on TripAdvisor. Users rate 1-star hotels differently according to the country, and in some countries this is not the worst score on average as can be seen in Figure 1 but these results should be analysed carefully because, specially in Austria, Poland, and Portugal the percentage of 1-star hotels of the sample is very low.

Only 1-star and 2-star hotels in seven European countries analysed and 1-star and 3-star hotels in four countries analysed show similarities in the average score of users, a fact that indicates customers do not perceive significant differences in the qualities of these hotels categories. As confirmed by Minazzi (2010), some European countries such as France and Italy have created two main groups: one for the lower categories (1, 2 and 3-star hotels), and another for higher categories (4 and 5-star hotels), which is a good proposal looking at our findings that hotels of the lower categories show similarities in the average score of users.

It could be due to the value for money, as confirmed by Martin-Fuentes (2016) there is a relationship between price and hotel category, so the ratings posted by past users could be affected by perceived value received.

Table 2 shows that, in general, the higher a hotel category is, the higher score it obtained as awarded by past users on TripAdvisor. From this we can conclude that the hotel system classification is a good source of information despite studies indicating that the star classification system criteria are obsolete (Torres et al., 2014) or that there is a necessity to implement policies to unify the hotel classification system in Europe to let the hotel stars "shine again" (Arcarons i Simon et al., 2008). Therefore it is demonstrated in this study that the overall quality of hotels can be inferred from their stars in line with Fang et al., (2016).

In general, the consumer confirms the validity of the hotel classification system determined by different rules and regulations in Europe. With each additional star category, a hotel presents a higher level of user satisfaction, as measured by the assessment given on TripAdvisor. So the results show that the hotel classification system adequately fulfills its function as customer ratings increase with each additional star.

Previous studies indicate that customers of hotels in higher categories are more demanding and quality is associated with service according to customer expectations, rather than the category of the establishment (López Fernández & Serrano Bedia, 2004). However, our study supports the idea that there is a relationship between the hotel category and user satisfaction.

The United Kingdom shows a different pattern in the mean score in 1-star and 2-stars. Because 1-star hotels are better rated than 2-star hotels, it could be linked to the research conducted by Callan (1995) that found that customers of 1-star and 2-star hotels in the United Kingdom use ratings systems less often than those staying in 3-star to 5-star hotels.

This finding could help the industry to closer fit the classification systems with the online reviews in order to include UGC to future classification systems to be consistent with customer needs (Blomberg-Nygard & Anderson 2016).

6. Conclusions

Differences of criteria in the allocation of hotel categories in European countries, even though they differ among regions inside the same country, do not present a problem, as there is a relationship between the category of a hotel and user satisfaction. This is evident from the point of view of the score awarded by past guests on TripAdvisor since higher category hotels have been given better scores by customers.

It can be concluded that as the stars in hotels serve to segment customers (Dioko et al. 2013), the opinions of customers are also a source of segmentation that allows better positioning of each hotel.

Given the importance acquired by COP and the online travel reviews as a source of information for making reservations at a hotel (Xiang & Gretzel, 2010) and that some research claims there are more flexible regulations for the hotel classification system (Arcarons i Simon et al., 2008), regulations could take into account UGC for the allocation of hotel stars, and, thus, avoid criteria that can become outdated with the passage of time.

From the point of view of hotel management, these findings highlight the importance of a hotel classification system. Seeing that more than 20,000 hotels in Europe do not have stars assigned on TripAdvisor, it is recommended that consumers be aware of the information provided, not only on websites, blogs, ads or social networks controlled by them, but also by the different online distribution channels and other COPs, such as TripAdvisor. As claimed by Denizci Guillet & Law (2010), in some cases the stars differ from reality which can confuse users and damage the reputation of the hotel.

The main singularity of this study is the big data analytics as we analysed most hotels in nine European countries on TripAdvisor, so the results would be impossible to obtain with survey studies.

Finally, as all investigations this is not without limitations. The data obtained allow us to draw conclusions for TripAdvisor only. Although TripAdvisor is very popular and has a large number of reviews, it may be biased in relation to nationalities using the website. Therefore, empirical replications with data obtained from other traveller opinion websites could bring greater insight into the discussion.

References

ABRATE, G., CAPRIELLO, A., & FRAQUELLI, G. (2011). When quality signals talk: Evidence from the Turin hotel industry. *Tourism Management*, *32*(4), 912–921. http://doi.org/10.1016/j.tourman.2010.08.006

ANDERSON, C. K. (2012). The Impact of Social Media on Lodging Performance. *Cornell Hospitality Report*, *12*(15), 4–11. Retrieved from http://www.budigitalhub.com/sites/default/files/white_papers/HotelsSocialMedia.pdf

ANDERSON, E. W. (1998). Customer Satisfaction and Word of Mouth. *Journal of Service Research*, *1*(1), 5–17. http://doi.org/10.1177/109467059800100102

ARCARONS I SIMON, R., GOITIA SERRA, V., & GONZÁLEZ AZNAR, N. (2008). La clasificación hotelera en la Unión Europea: Un mercado poco común. *Papers de Turisme*, (43–44), 49–67.

ARNDT, J. (1967). Role of product-related conversations in the diffusion of a new product. *Journal of Marketing Research*, 291–295.

AYEH, J. K., AU, N., & LAW, R. (2013). "Do We Believe in TripAdvisor?" Examining Credibility Perceptions and Online Travelers' Attitude toward Using User-Generated Content. *Journal of Travel Research*, *52*, 437–452. http://doi.org/10.1177/0047287512475217

BALAGUÉ, C., MARTIN-FUENTES, E., & GÓMEZ, M. J. (2016). Fiabilidad de las críticas hoteleras autenticadas y no autenticadas: El caso de TripAdvisor y Booking.com. *Cuadernos de Turismo*, *38*, 63–82. http://doi.org/http://dx.doi.org/10.6018/turismo.38.271351 Universidad

BLOMBERG-NYGARD, A., & ANDERSON, C. K. (2016). United Nations world tourism organization study on online guest reviews and hotel classification systems: an integrated approach. *Service Science*, *8*(2), 139–151.

CALLAN, R. J. (1995). Hotel classification and grading schemes, a paradigm of utilisation and user characteristics. *International Journal of Hospitality Management*, *14*(3), 271–283.

CASALO, L. V., FLAVIAN, C., GUINALIU, M., & EKINCI, Y. (2015). Do online hotel rating schemes influence booking behaviors? *International Journal of Hospitality Management*, *49*, 28–36.

CEZAR, A., & ÖGÜT, H. (2016). Analyzing conversion rates in online hotel booking. *International Journal of Contemporary Hospitality Management*, *28*(2), 286–304. http://doi.org/10.1108/IJCHM-05-2014-0249

CHEN, Y.-F., & LAW, R. (2016). A Review of Research on Electronic Word-of-Mouth in Hospitality and Tourism Management. *International Journal of Hospitality & Tourism Administration*, *17*(4), 347–372. http://doi.org/10.1080/15256480.2016.1226150

DE ASCANIIS, S., & GRETZEL, U. (2012). What's in a review title? In M. Fuchs, F. Ricci, & L. Cantoni (Eds.), *Information and Communication Technologies in Tourism* (pp. 460–470). New York, NY: Springer.

DENIZCI GUILLET, B., & LAW, R. (2010). Analyzing hotel star ratings on third - party distribution websites. *International Journal of Contemporary Hospitality Management*, *22*(6), 797–813. http://doi.org/10.1108/09596111011063098

DIOKO, L. A. N., SO, S.-I. (AMY), & HARRILL, R. (2013). Hotel category switching behavior—Evidence of mobility, stasis or loyalty. *International Journal of Hospitality Management*, *34*, 234–244. http://doi.org/10.1016/j.ijhm.2013.04.002

FANG, B., YE, Q., KUCUKUSTA, D., & LAW, R. (2016). Analysis of the perceived value of online tourism reviews: Influence of readability and reviewer characteristics. *Tourism Management*, *52*, 498–506. http://doi.org/10.1016/j.tourman.2015.07.018

GUO, Y., BARNES, S. J., & JIA, Q. (2017). Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent dirichlet allocation. *Tourism Management*, *59*, 467–483. http://doi.org/http://dx.doi.org/10.1016/j.tourman.2016.09.009

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? *Journal of Interactive Marketing*, *18*(1), 38–52. http://doi.org/10.1002/dir.10073

HOTELSTARS UNION. (2017). Strategic Partnership for Hotel Classification in Europe. Retrieved September 25, 2017, from https://www.hotelstars.eu/fileadmin/Dateien/PORTAL_HSU/Factsheet_01_17.pdf

HOTREC. (2015). Hotrec. Retrieved from http://www.hotrec.eu/newsroom/press-releases-1714/hotelstars-union-polished-the-criteria-for-its-hotelstars-categories.aspx

KIM, W. G., & PARK, S. A. (2017). Social media review rating versus traditional customer satisfaction. *International Journal of Contemporary Hospitality Management*, *29*(2), 784–802. http://doi.org/10.1108/IJCHM-11-2015-0627

LITVIN, S. W., GOLDSMITH, R. E., & PAN, B. (2008). Electronic word-of-mouth in hospitality and tourism management. *Tourism Management*, *29*(3), 458–468. http://doi.org/10.1016/j.tourman.2007.05.011

LIU, B., PENNINGTON-GRAY, L., DONOHOE, H., & OMODIOR, O. (2015). New York City Bed Bug Crisis as Framed by Tourists on Tripadvisor. *Tourism Analysis*, *20*(2), 243–250. http://doi.org/10.3727/108354215X14265319207597

LÓPEZ FERNÁNDEZ, M. C., & SERRANO BEDIA, A. M. (2004). Is the hotel classification system a good indicator of hotel quality? *Tourism Management*, *25*(6), 771–775. http://doi.org/10.1016/j.tourman.2004.06.007

MARTIN-FUENTES, E. (2016). Are guests of the same opinion as the hotel star-rate classification system? *Journal of Hospitality and Tourism Management*, *29*, 126–134. http://doi.org/10.1016/j.jhtm.2016.06.006

MARTIN-FUENTES, E., DARIES-RAMON, N., & MARINÉ-ROIG, E. (2015). Satisfacción y fuentes de información de los estudiantes de movilidad universitarios. *Opción*, *31*(Especial 2), 712–729.

MARTIN-FUENTES, E., FERNANDEZ, C., MATEU, C., & MARINE-ROIG, E. (2018). Modelling a grading scheme for peer-to-peer accommodation: Stars for Airbnb. *International Journal of Hospitality Management*, *69*, 75–83. http://doi.org/10.1016/j.ijhm.2017.10.016

MARTIN-FUENTES, E., MATEU, C., & FERNANDEZ, C. (2018). The more the merrier? Number of reviews versus score on TripAdvisor and Booking.com. *International Journal of Hospitality & Tourism Administration*, in press. http://doi.org/10.1080/15256480.2018.1429337

MELIÁN-GONZÁLEZ, S., BULCHAND-GIDUMAL, J., & GONZÁLEZ LÓPEZ-VALCÁRCEL, B. (2013). Online customer reviews of hotels: As participation increases, better evaluation is obtained. *Cornell Hospitality Quarterly*, *54*(3), 274–283.

MINAZZI, R. (2010). Hotel classification systems: a comparison of international case studies. *Acta Universitatis Danubius. Œconomica*, *6*(4), 64–86.

NARANGAJAVANA, Y., & HU, B. (2008). The Relationship Between the Hotel Rating System, Service Quality Improvement, and Hotel Performance Changes: A Canonical Analysis of Hotels in Thailand. *Journal of Quality Assurance in Hospitality & Tourism*, *9*(1), 34–56. http://doi.org/10.1080/15280080802108259

NÚÑEZ-SERRANO, J. A., TURRIÓN, J., & VELÁZQUEZ, F. J. (2014). Are stars a good indicator of hotel quality? Assymetric information and regulatory heterogeneity in Spain. *Tourism Management*, *42*, 77–87. http://doi.org/10.1016/j.tourman.2013.10.004

ÖĞÜT, H., & ONUR TAŞ, B. K. (2012). The influence of internet customer reviews on the online sales and prices in hotel industry. *The Service Industries Journal*, *32*(2), 197–214. http://doi.org/10.1080/02642069.2010.529436

PACHECO, L. (2017). Customer Satisfaction in Portuguese Hotels: Evidence for Different Regions and Hotel Segments. *Tourism Analysis*, *22*(3), 337–347. http://doi.org/10.3727/108354217X14955605216087

RAGUSEO, E., & VITARI, C. (2017). The Effect of Brand on the Impact of e-WOM on Hotels' Financial Performance. *International Journal of Electronic Commerce*, *21*(2), 249–269.

TALIAS, M. (2016). Voluntary hotel regulation as a political compromise. *International Journal of Hospitality Management*, *56*(Supplement C), 10–17. http://doi.org/https://doi.org/10.1016/j.ijhm.2016.04.007

TORRES, E. N., ADLER, H., & BEHNKE, C. (2014). Stars, diamonds, and other shiny things: The use of expert and consumer feedback in the hotel industry. *Journal of Hospitality and Tourism Management*, *21*, 34–43. http://doi.org/10.1016/j.jhtm.2014.04.001

TRIPADVISOR. (2014). TripAdvisor Help Center. Retrieved May 13, 2016, from https://www.tripadvisorsupport.com/hc/en-us/articles/200614057

TRIPADVISOR. (2017). TripAdvisor, Media Center. Retrieved September 4, 2017, from https://tripadvisor.mediaroom.com/

TUSSYADIAH, I. P., & ZACH, F. (2017). Identifying salient attributes of peer-to-peer accommodation experience. *Journal of Travel & Tourism Marketing*, *34*(5), 636–652. http://doi.org/10.1080/10548408.2016.1209153

XIANG, Z., DU, Q., MA, Y., & FAN, W. (2017). A comparative analysis of major online review platforms: Implications for social media analytics in hospitality and tourism. *Tourism Management*, *58*, 51–65. http://doi.org/10.1016/j.tourman.2016.10.001
XIANG, Z., & GRETZEL, U. (2010). Role of social media in online travel information search. *Tourism Management*, *31*(2), 179–188. http://doi.org/10.1016/j.tourman.2009.02.016
XIANG, Z., SCHWARTZ, Z., GERDES, J. H., & Uysal, M. (2015). What can big data and text analytics tell us about hotel guest experience and satisfaction? *International Journal of Hospitality Management*, *44*, 120–130.
YEN, C.-L. (ALAN), & TANG, C.-H. (HUGO). (2015). Hotel attribute performance, eWOM motivations, and media choice. *International Journal of Hospitality Management*, *46*, 79–88. http://doi.org/10.1016/j.ijhm.2015.01.003

8. Modelling a grading scheme for peer-to-peer accommodation: Stars for Airbnb

Pages 115 to 136 contain this article:

Martin-Fuentes, E., Fernandez, C., Mateu, C., & Marine-Roig, E. (2018). Modelling a grading scheme for peer-to-peer accommodation: Stars for Airbnb. *International Journal of Hospitality Management*, 69, 75-83.

Journal Metrics

Journal Citation Report (Clarivate Analytics, 2018)
Year 2017 First Quartile
Subject area: Hospitality, Leisure, Sport and Tourism. Rank 7 of 50
Impact Factor: 3.445
5-Year Impact Factor: 4.664

CiteScore: 4.10

SCImago Journal Rank (SJR): 2.027
Year 2017 First Quartile
Area: Business, Management and Accounting. Rank 78 of 1,605
Subject area: Tourism, Leisure and Hospitality Management. Rank 5 of 101

International Journal of Hospitality Management 69 (2018) 75–83

ELSEVIER

Contents lists available at ScienceDirect

International Journal of Hospitality Management

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

Discussion paper

Modelling a grading scheme for peer-to-peer accommodation: Stars for Airbnb

Eva Martin-Fuentes[a,*], Cesar Fernandez[b], Carles Mateu[b], Estela Marine-Roig[a]

[a] Department of Business Administration, University of Lleida, C/Jaume II, 73, 25001, LLEIDA, Spain
[b] INSPIRES Research Institute, University of Lleida, C/Jaume II, 69, 25001, LLEIDA, Spain

8.1. Introduction

The opportunistic behaviors of information asymmetry can be avoided by guarantees or by external auditors' certifications (Stiglitz, 2002). In the hospitality industry, information asymmetry can also be prevented by price, customer review ratings, and the number of recommendations, among others (Cezar & Ögüt, 2016; Neirotti et al., 2016; Öğüt & Onur Taş, 2012). Moreover, star-rating classification systems established by third-party institutions serve as a tool to mitigate asymmetric information (Nicolau & Sellers 2010; Núñez-Serrano et al., 2014). Besides the problem of information asymmetry, sharing economy establishments may face the problem of information overload caused by UGC, which is key to the way they operate and also to the trust system. This excess of information can complicate the decision-making process (Fang et al., 2016; Marine-Roig, 2017) because it is not possible to read all the reviews that can be found on websites. In this respect, simplified integrative classification systems understandable worldwide, such as hotel categories, could also help users overcome the information overload.

This study aims to infer the hotel categories from UGC and other parameters that are not taken into account by the institutions in charge of assigning the categories and, then, to create a model to classify the properties offered by P2P accommodation platforms, similar to grading scheme categories for hotels, thus preventing opportunistic behaviors of information asymmetry and helping users filter the information overload.

8.2. Contribution to the state-of-the-art

The main finding of this research is that the hotel category can be predicted by parameters related to UGC and to others that are different from those used by the norms of public and private institutions in charge of regulating the hotel classification system. The accuracy of the prediction is higher with machine learning techniques such as Support Vector Machines (SVMs) than with traditional techniques such as logistic regression.

This prediction has various implications. For example, the bureaucracy related to the hotel classification system could be reduced as the number of audits to check whether the criteria are met to keep or to lose a star would be minimized; it could facilitate the convergence of different systems worldwide to help users understand hotel categories internationally, with a system that is easily understood by all; and the system would match users' points of view, since the best or the ideal classification system would be the one adapted to the users' needs, and that is what this model proposes in order to help increase transparency in consumer decision-making.

In this respect, we apply the results to P2P platforms that have an intrinsic link with UGC. Such UGC is an essential part of how they work, and without it their business models defined as "engagement platforms" would not exist (Breidbach & Brodie, 2017). However, it is important to highlight that this model would allow different types of accommodation (hotels, private rentals, etc.) to be compared using the same classification system. Lastly, this system also provides valuable information about the importance of features when classifying lodging properties. The most important feature is price, followed by location and cleanliness.

8.3. Journal paper

Modelling a grading scheme for P2P accommodation: Stars for Airbnb

Eva Martin-Fuentes*[a], Cesar Fernandez[b], Carles Mateu[b] and Estela Marine-Roig [a]
University of Lleida

[a] Department of Business Administration.
E-mail: eva@aegern.udl.cat estela.marine@aegern.udl.cat
[b] INSPIRES Research Institute.
E-mail: cesar@diei.udl.cat carlesm@diei.udl.cat
University of Lleida. C/ Jaume II, 73, 25001 LLEIDA, Spain.
Telephone number: + 34 973 703216
*corresponding author

Abstract
This study aims, firstly, to determine whether hotel categories worldwide can be inferred from features that are not taken into account by the institutions in charge of assigning such categories and, if so, to create a model to classify the properties offered by P2P accommodation platforms, similar to grading scheme categories for hotels, thus preventing opportunistic behaviours of information asymmetry and information overload. The characteristics of 33,000 hotels around the world and 18,000,000 reviews from Booking.com were collected automatically and, using the Support Vector Machine classification technique, we trained a model to assign a category to a given hotel. The results suggest that a hotel classification can usually be inferred by different criteria (number of reviews, price, score, and users' wish lists) that have nothing to do with the official criteria. Moreover, room prices are the most important feature for predicting the hotel category, followed by cleanliness and location.

Keywords: Airbnb; hotel classification system; Support Vector Machine; big data; peer-to-peer accommodation platform

1. Introduction

The sharing economy is defined as "an economic system based on sharing underused assets or services, for free or for a fee, directly from individuals" (Botsman and Rogers, 2011), and it is significantly changing consumption patterns (Byers et al., 2013). In tourism, the sharing economy is not a new phenomenon because this peer-to-peer (P2P) exchange has existed for a long time with, for example, the typical advertisement "For rent" hanging from beach apartments, with the owners directly offering short-term rentals or short stays to others, or with individuals waiting for backpackers to arrive at bus stations to offer them a room in their home to get extra income.

With the advance of the Internet, the tourist accommodation sector is experiencing a revolution (Cheng, 2016), with businesses such as Couchsurfing, HomeExchange, Airbnb, HomeAway or Roomorama acting as intermediaries to facilitate contact between host and guest in a simple, convenient and fast way, allowing hosts to earn extra income (Sigala, 2015).

One of the detected barriers to using P2P accommodation platforms is the lack of trust (Tussyadiah and Pesonen, 2016), so overcoming this barrier is a challenge for these platforms and for people who offer their properties for use by others. This lack of trust is related to information asymmetry, which is generated in any market. This theory, developed by Akerlof (1970) in "The Market for Lemons" explains that the seller (i.e., host) knows exactly the true state of the service offered (apartment, room, studio) and the purchaser (guest) does not know it and does not trust in it. Thus, poor services drive out good quality services from the market, leading to an adverse selection problem that ends up negatively affecting those who offer quality services but are drawn down by those who do not provide good service. There are different ways to avoid the adverse effects of information asymmetry such as transmitting credible information. An example of this is when sellers offer post-sales warranties, since only those sellers who are sure of their products would offer them (Stiglitz, 2002). In this sense, the more information available about their services and the more accurate it is, the more people will be willing to use such services (Harford, 2010).

Moreover, with the huge amount of information generated on the Internet for a single item, e.g., thousands of reviews for a single company or destination, an additional problem of information overload may occur, where users find it impossible to sift out useful or high-quality information or to read all opinions (Marine-Roig, 2017). As a consequence, they become overwhelmed. This issue is also a barrier to P2P consumption as it makes decision-making more difficult.

Thus, and given that hotel classification compensates for information asymmetry (Martin-Fuentes, 2016; Nicolau and Sellers, 2010; Öğüt and Onur Taş, 2012), it can help to reduce the problem of information overload. The aim of this study is to predict a hotel category by taking into consideration certain user-generated content (UGC) parameters and other factors in order to create a model to classify the properties offered by P2P accommodation platforms, similar to grading scheme categories of hotels, driven by the need to provide users with certain guarantees for such accommodation services, thereby allowing them to trust in them and preventing opportunistic behaviours of information asymmetry. This model is applied to Airbnb, the leading platform in the P2P accommodation sector, based on information extracted from 18,000,000 reviews on Booking.com written by guests staying at any of 33,000 hotels in outstanding international destinations.

In order to establish a model to classify accommodation on sharing economy platforms, the Support Vector Machine classification technique developed by Vapnik (1995) will be used. The technique is explained in detail in the existing literature, and although its application has been proven in fields such as medicine, engineering, biology, marketing and others, it has not been widely used in the field of tourism (Akin, 2015; Zheng and Ye, 2009), despite the good results reported.

2. Literature review

This section reviews the collaborative economy with special emphasis on the accommodation sector. The importance of hotel classification in order to avoid information asymmetry and information overload is also reviewed.

2.1. Sharing economy

The sharing economy is a phenomenon that can be considered a consequence of the global financial crisis that began in the late 2000s (Buczynski, 2013). It has exploded in recent years thanks to the information and communication technologies (ICTs) that have enabled purchasers and sellers to get in touch with each other directly and conveniently.

Collaborative consumption, or the sharing economy, promotes the use of goods and services without having ownership of them. In the case of property, ownership is increasingly being replaced by use (Rifkin, 2000). Also called the peer-to-peer (P2P) economy, in collaborative consumption, individuals participate in sharing activities by renting, lending, trading, bartering or swapping goods, services, transportation solutions, space or money (Möhlmann, 2015).

In tourism, P2P platforms have experienced tremendous growth. This applies not only to platforms related to the accommodation sector, but also to those related to the catering, transport and tour-guide sectors (Cheng, 2016). The factors that have led to an increase in the use of these new forms of accommodation are economic, because they are potentially cheaper for travellers than other kinds of accommodation (Guttentag, 2015; Tussyadiah and Pesonen, 2016), social, especially because they allow travellers to be in touch with the local community, and others such as authenticity and sustainability (Botsman and Rogers, 2011; Sigala, 2015; Tussyadiah and Pesonen, 2016), because excessive consumption and unnecessary purchases of products that subsequently will not be used can be avoided by sharing goods (Bulchand Gidumal and Melián González, 2016).

Tussyadiah and Pesonen (2016), in an exploratory study with American and Finnish travellers, found that, among Americans, trust is a barrier to using P2P accommodation (not only trust in hosts but also in technology and transaction safety) and conclude that a significant challenge for P2P accommodation companies is the need to create a mechanism of trust among customers, for example, by including reputation scoring or other consumer protection measures such as safe and secure transaction systems.

In this respect, as Ert et al. (2016) claim, P2P product platforms involve economic risks only, while sharing a home involves additional risks. Moreover, “risks are higher for transactions involving products whose attributes can be evaluated only after purchase and use” (Ba and Pavlou, 2002: 12). Therefore, sharing economy platforms base the way they operate and also their trust system on P2P communication through UGC (Tussyadiah and Zach, 2017). Barriers to creating and consuming UGC have been lowered dramatically

(Ayeh et al., 2013). Personal thoughts and opinions posted by users are easily accessible to the global community (Dellarocas, 2003) and potentially affect travellers' decisions in terms of creating ideas and reducing alternatives (Barreda and Bilgihan, 2013). Indeed, many studies have demonstrated the influence that UGC in general and online travel reviews in particular have on travel-related decisions through the electronic Word-of-Mouth (eWOM) effect (Schuckert et al., 2015). Social media is a particularly powerful and credible source of information among users, and especially among digital natives.

Consumers' opinions have been found to generate more confidence than communications from a company (Gretzel and Yoo, 2008; Vermeulen and Seegers, 2009). Although some users are afraid of biased information and false comments (Blomberg-Nygard and Anderson, 2016; Hensel and Deis, 2010), the reality is that most users trust social media reviews (Pirolli, 2016), and this is demonstrated by their travel-related behaviour, searching for online advice or information before making reservations (Blomberg-Nygard and Anderson, 2016; Kim et al., 2011). Thus, online opinions are essential not only for a sharing economy service, but also for the traditional hotel sector (Guttentag, 2015), and should be included in future classification systems to be consistent with customer needs (Blomberg-Nygard and Anderson, 2016). Moreover, online reviews are useful for promoting properties –especially the less-known ones– (Vermeulen and Seegers, 2009) and for taming the possible adverse effects of asymmetric information (Ba and Pavlou, 2002; Park and Nicolau, 2015).

2.2 Information asymmetry, information overload and star-rating classification system

In a market where one of the parties involved in a buying/selling transaction does not have the same information as the other about a product or service, so-called information asymmetry occurs, which could cause the market to fail (Akerlof, 1970).

There are different mechanisms to avoid opportunistic behaviours of information asymmetry, such as guarantees of certain claims that only those sellers who are confident in the quality of their products would offer, or certification by external auditors to ensure the quality of the product or service (Stiglitz, 2002).

Hotel customers rely on recommendations by friends and family to solve their informational disadvantage because tourism services cannot be tried or tested before purchase (Fernández-Barcala et al., 2010). To some extent, this has been replaced by the role of the travel agent, who acts as an intermediary in a market characterised by such asymmetry (Clerides et al., 2005; Jeacle and Carter, 2011).

Information asymmetry in the hospitality industry can also be countered using other elements such as price, customer review ratings, number of recommendations and average display rank (Cezar and Ögüt, 2016; Martin-Fuentes, 2016; Neirotti et al., 2016; Öğüt and Onur Taş, 2012). Moreover, star-rating classification systems established by third party institutions serve as a tool to mitigate asymmetric information (Martin-Fuentes 2016; Nicolau and Sellers 2010; Núñez-Serrano et al., 2014) and provide guidelines for reducing the hotel booking risk (Neirotti et al., 2016).

In addition to the problem of information asymmetry, sharing economy establishments may face the problem of information overload caused by UGC, which is key to the way they operate and also to the trust system. In travel and hospitality, online travel reviews have increased exponentially and there is usually a huge number of reviews available for the same product or service (De Ascaniis and Gretzel, 2012). However, increased amounts of information can be both a blessing and a curse (O'Connor, 2010). Although UGC information provides users with unbiased, unsolicited and cost-effective data on products and services, information overload may actually prevent consumers from getting a comprehensive idea or high-quality information and, moreover, can complicate the decision-making process (Fang et al., 2016; Marine-Roig, 2017). Therefore, given that it is impossible for users to read all reviews about a product or service, it is crucial for them to have simplified, uniform and comparable indicators available. In this respect, simplified integrative classification systems, easily understood by all, such as accommodation star-rating levels or simplified indicators, could also help users overcome the information overload.

However, no grading scheme categories similar to hotel classifications exist in the case of P2P accommodation. Hotel classification systems are established using various standards set by governments or by independent organisations. These systems are universally recognised, and the most common method for classifying hotels is to rank them from 1 to 5 stars, although the requirements for assigning the stars differ depending on the institutions responsible for doing so, which can be split into official and non-official (Zhan-Qing and Liu, 1993).

The star-rating classification mechanism is the most common customer segmentation pattern in the hotel industry (Dioko et al., 2013); hotel quality can be inferred from the number of stars (Fang et al., 2016), the highest hotel categories can be considered as an indicator of high quality (Abrate et al., 2011), and it plays a general role in the selection of hotels (Callan 1998; Núñez-Serrano et al., 2014). Furthermore, although the star-rating classification systems are different all over the world, it has been proven that there is a relationship between star-rating classification and satisfaction measured from the point of view of scores assigned by users (Martin-Fuentes et al., 2016).

However, the current hotel star-rating classification system presents some weaknesses. The hotel classification system does not follow the same pattern all over the world as each country has its own criteria. At the European level, attempts to launch a process of harmonisation of different regulations have nevertheless been made (Arcarons i Simon, 2008).

There is an initiative by hotel associations from some European countries, sponsored by the Hotrec Association (Hotels, Restaurants & Cafes in Europe), that is trying to implement a scoring system to enable the unification of criteria for the allocation of stars in different countries (Hotrec, 2015), but it is not an easy task because, even within an individual country, there are different systems in place. This is the case for Spain, which has 17 different classification systems, one for each of the autonomous governments that have the power to regulate in this field.

Moreover, the current hotel classification system does not take into account guests' opinions in the form of UGC. Such increasingly popular UGC, which has now become central to accommodation bookings (Blomberg-Nygard and Anderson, 2016), would provide a quality check on the amenities and characteristics required for the classification system. Thus, Blomberg-Nygard and Anderson (2016) suggest that future hotel classification systems should be refined by integrating online reviews into them. The idea of integrating online travel reviews in P2P accommodation classification systems is even stronger because UGC production and user opinions are at their very core. This is so because P2P platforms are online "engagement platforms", whose operation and success is based on value co-creation, information exchange and the production of UGC, among various economic actors in a service ecosystem (Breidbach and Brodie, 2017).

3. Research aim and methodology

This study aims, firstly, to determine whether a hotel classification system can be inferred in general from criteria and standards that are not considered by the rules and regulations of public and non-public organisations in charge of assigning hotel categories and, if so, to use this model to design a classification system for P2P accommodation platforms in order to avoid a market of "lemons" and information overload and to use it on platforms like Airbnb, which are based on user interaction and value co-creation.

In order to contribute to the P2P accommodation literature and, by so doing, to provide additional insights, this study aims to answer this research question: Is it possible to design a classification system for P2P accommodation platforms similar to the hotel classification system in order to avoid a market of "lemons" and information overload on P2P platforms like Airbnb?

As seen in the literature review, the problems of a lack of trust arising from asymmetric information can cause businesses and even markets to collapse, so it is necessary to provide a mechanism that offers its users certain guarantees. Similarly, to address the problems arising from UGC information overload, indicator classification systems that are both comprehensive and simple are needed.

The conclusions by (Ert et al., 2016: 72) state that "the strong need for trust in sharing economy platforms leads consumers to use any information available to them" and the literature review confirms that, on the one hand, hotel star-ratings counter the adverse effects of asymmetric information and, on the other, the hotel classification system is internationally recognised (despite being applied differently in each country); it is a comprehensive system that can help simplify tourists' decision-making. Moreover, within a context of the ever-increasing popularity of UGC, integrated classifications should combine hotel classification systems focusing on objective features and on guest reviews – providing information about how service-related elements are perceived – since both are complementary (Blomberg-Nygard and Anderson, 2016). In fact, "both consumers and the industry are interested in seeing a closer fit between the two" so that offerings are presented in keeping with consumer needs (Blomberg-Nygard and Anderson, 2016: 3). Therefore, and responding to these needs, the merging of hotel-like classifications with UGC could provide users with a holistic integrative classification system capable of preventing online information overload.

So, on that basis, we try to build a model to classify P2P accommodation that increases customer trust, integrates several elements and is easy to understand worldwide. In this sense, we propose building a simple model for P2P accommodation platforms that consumers can trust, similar to the hotel classification system. The proposed classification model is applied to the leading P2P accommodation platform Airbnb, though it could be used for any other P2P platform.

3.1 Case study: Airbnb

The proposed classification model is applied to the P2P accommodation platform Airbnb. Among P2P accommodation services, Airbnb, founded in 2008, is an example of a leading company that offers properties in 194 countries worldwide (Airbnb, 2016a). Airbnb is a company that bases its business model on putting individuals who have a space for rent in contact with other individuals who want to rent it for a period of time in exchange for money, all of which is done via the Internet. Airbnb is the best-known P2P accommodation community marketplace platform, with more than 34,000 cities, 60 million guests and 2 million listings (Airbnb, 2016a). It can be considered a sharing economy engagement platform based on user interaction and value co-creation (Breidbach and Brodie, 2017). Airbnb connects travellers with local hosts that provide a space, which can be entire properties, castles, rooms, beds, sofas, airbeds or any kind of accommodation. The way it works is that guests contact hosts through the Airbnb platform to confirm availability and to get more information through the messaging system. Airbnb charge the guests and holds their money until 24 hours after the check in, to allow guest and host to confirm that everything is in order, and later on Airbnb transfers the money to the host.

As previously seen, trust management in P2P platforms like Airbnb is a critical element of their business, which the company knows and announces with the slogan “Trust is what makes it work”. Airbnb uses a reputation mechanism that allows hosts and travellers to write reviews about each other; a review is based on a previous stay, and is done within 14 days after that stay. Moreover, guests and hosts can scan a government ID to verify their online profiles, and there is a secure messaging system and a host guarantee to cover any possible damage to the property (Airbnb, 2016b).

In addition, Airbnb uses a quality certification called ‘Superhost’ that serves to prevent opportunistic behaviours of information asymmetry and information overload. However, the percentage of properties that have the ‘Superhost’ badge on Airbnb is very limited (e.g., a mere 2.9% in Hong Kong) (Liang et al., 2017).

This reputation system, in which both the service supplier and the service demander can give their opinions about each other, has also been applied by other collaborative economy companies such as Couchsurfing or BlaBlaCar and can make people think twice before posting a bad review because of fear of revenge (Ert et al., 2016). To avoid it, Airbnb does not publish reviews until both parties have given their opinions or until the deadline has expired to do so.

3.2 Data collection

To create a classification model applicable to P2P accommodation platforms similar to the hotel star-rating classification system, in this study, data is taken from Booking.com because it is a prominent example of an online accommodation-booking website. It has 895,589 properties in 224 countries and deals with over 1 million room-night reservations per day (Booking.com, 2016). On Booking.com, travellers can compare prices and customer reviews (Neirotti, 2016) and it is a popular online source for hotel information (Sun et al., 2015) that draws the attention of researchers.

Moreover, Booking.com and Airbnb have some similarities, apart from being leaders in accommodation reservations; both websites allow customers to give their opinions and have similar systems for collecting them. Thus, both websites only allow users to leave a review if someone has booked accommodation through the respective site and actually stays at the reviewed property, so all are “verified reviews from real people”, as Booking.com claims.

As mentioned above, the way both websites collect reviews is similar; after a stay, the user receives an e-mail to rate the property and to post a review, the time to rate the property is limited (for Booking.com it is 28 days and for Airbnb it is 14 days) to avoid out-dated opinions.

On Booking.com, users rate 6 items (value, cleanliness, location, services, comfort and staff) and, on Airbnb, users also rate 6 items (value, cleanliness, location, check in, communication and accuracy), the common variables (value, cleanliness, and location) were taken into account in this study.

The selection of these variables and not others to create a star-rating system for P2P accommodation is also justified by the preferences of sharing economy guests compared to those of hotel guests. As emphasized by Tussyadiah and Zach (2017), cleanliness and location are fundamental elements for both types of guest. However, P2P accommodation guests place much greater value on location and social interactions with hosts than hotel guests do. For the latter, convenience and room features are more important (Belarmino et al., 2017; Tussyadiah and Zach, 2017). Earlier studies have matched or compared hotels and P2P accommodation based on price, among other aspects (Belarmino et al., 2017). Value for money was found to be a fundamental driver of booking P2P accommodation, as well as a basic element of satisfaction therewith (Belarmino et al., 2017), since emphasis was placed on this type of accommodation providing better value than hotels did (Harrington, 2015). As a result, cleanliness, location and price should be taken as the core indicators of P2P accommodation analyses.

In April 2016, we automatically gathered the hotel data from Booking.com; the number of reviews, the general scoring, the score for the 6 items, the hotel name, the city, the country, the number of users that saved the hotel in their wish list, the hotel category and the price (ranked from 1 to 5 on Booking.com). The hotels in the world's 443 top destinations according to TripAdvisor were classified into four regions: Europe (EUR), America (AME), Asia and Pacific (ASP), and the Middle East and Africa (MEA) as suggested by Banerjee and Chua (2016), as shown in Table 1.

The data was collected using an automatically controlled web browser (developed in Python) that simulates user navigation (clicks and selections).

We filtered the results by "Property type", selecting "Hotels" and "Review score", with the rated by "All reviewers" option.

Table 1. Data collection by regions

Region	Countries	Destinations	Hotels	Reviews
EUR	17	168	14,395	11,097,703
AME	23	122	7,022	3,285,925
ASP	16	109	10,448	3,559,306
MEA	9	44	1,179	767,947
Total	65	443	33,044	18,710,881

3.3. Support Vector Machine

Support Vector Machines (SVMs) are a useful technique for binary data classification. By finding hyperplanes that separate n-dimensional data, they learn to separate data into two classes (Vapnik, 1995), turning the problem into a set of linear equations. A dataset is often not linearly separable, so the concept of kernel is introduced in SVMs. Different types of kernels may be devised, but the common idea is to cast the original data into a higher dimension dataset that may be separated. Some of the most successful kernels are Radial Basis Function (RBF) kernels, particularly when the number of features is not large, as in our case. RBF kernels are exponential functions defined by a single parameter, namely the exponent constant, being preferable to other types of kernels with a high number of parameters such as polynomials.

In our experiment, we use LIBSVM (CC01a), which is an open source implementation of SVMs written in C code.

When dealing with multiclass data (it should be noted that in our experiment the instances belong to five classes according to the hotel star classification), LIBSVM implements multiclass classification using one-against-all methods (Hsu and Lin, 2002). Having k classes $\binom{k}{2}$, binary classifiers are constructed. Then, each point to be predicted is classified according to each of the binary $\binom{k}{2}$ classifiers, giving one vote to the class (or classes) to which it has been assigned. Finally, the point is designated to the class with a higher number of votes received.

The decision to use SVM classifying techniques instead of more traditional techniques like an ordered logistic regression was due to some of the core advantages of SVM and because the results obtained with the ordered logistic model were worse, as shown in Table 2.

SVMs enable non-linear data to be easily classified, while providing a more robust model, thanks to the maximisation of the support vector margins (the distance to the separation hyperplane of the support values). It also provides a simple unique solution to the classification problem (whereas deep neural networks can offer multiple solutions to the same problem). Furthermore, it is computationally efficient and widely available (many statistical packages provide SVM implementations), so research reproducibility is guaranteed because it is not dependent on using the same code as that used in deep neural networks.

Because of these features, SVMs are widely used in pattern recognition problems: face and speech recognition, face detection and image recognition, financial classification, medical analytics, etc.

In short, SVMs are a supervised Machine Learning technique that creates a model from sample data (training set); using that model, its validity is then checked on testing data (validation set) to compute a predefined performance measure, called accuracy, which is the ratio of correctly classified instances.

4. Results

A classification task usually involves separating data into training and testing sets. Each instance in the training set contains one “target value” (i.e., the class labels) and several “attributes” (i.e., the features or observed variables). The goal of SVM is to produce a model (based on the training data) that predicts the target values of the test data given only the test data attributes (Hsu et al., 2003).

In our case, the number of classes is 5 when the 5 star-rating classification is used, or 4 when grouped categories are used (i.e. [1,2], [2-3], [3-4] and [4-5]). Regardless of the number of classes, the number of features employed is 6 (1: Cleanliness, 2: Value, 3: Location, 4: Reviews, 5: ListSaved, 6: Price), which are the 6 common features on Booking.com (from where we collected the data) and on Airbnb.

In order to avoid creating large datasets that make SVM computation unfeasible, raw data was split for the training and the testing phases into 10 sets for each region, and the results show the average over the 10 datasets. Furthermore, we have tried to balance the datasets, when possible, with the same number of instances for each class. For the training phase, in EUR we used 300 instances of 1-star and 900 of 2- to 5-star hotels for each of the 10 sets. In AME, we used 40 instances of 1-star and 500 of 2- to 5-star hotels; in ASP, 290 instances of 1-star and 1,000 of 2- to 5-star hotels; and, finally, in MEA, 20 instances of 1-star, 50 of 2-star and 200 of 3- to 5-star hotels.

The results show a high level of accuracy except for the 1-star hotel category in EUR, AME and ASP, and 2-star category in MEA, as shown in Table 2.

Table 2. Results for 5 star-rating classification

Region	Category	Test phase instances	Accuracy SVM	Ratio SVM	Ratio Logit
EUR	1	1,000	12	0.01	0.00
	2	1,000	729	0.73	0.77
	3	1,000	452	0.45	0.28
	4	1,000	371	0.37	0.39
	5	1,000	837	0.84	0.84
AME	1	500	0	0.00	0.00
	2	1,000	686	0.69	0.75
	3	1,000	442	0.44	0.26
	4	1,000	256	0.26	0.33
	5	1,000	876	0.88	0.87
ASP	1	1,000	28	0.03	0.00
	2	1,000	741	0.74	0.79
	3	1,000	363	0.36	0.19
	4	1,000	314	0.31	0.43
	5	1,000	841	0.84	0.82
MEA	1	200	74	0.37	0.00
	2	200	2	0.01	0.00
	3	200	151	0.76	0.15
	4	200	119	0.60	0.08
	5	200	153	0.77	0.17

Grouping the hotels into four categories as budget accommodation (1 and 2-star hotels), mid-low range accommodation (2- and 3-star hotels), mid-high range accommodation (3- and 4-star hotels), and superior accommodation (4- and 5-star hotels), the results improve because there is one category less. Worthy of note is that the training phase was done with the 5 categories coinciding with the 5 star-rating classification, but the results are explained in 4 categories, i.e., the categories in the training phase have not been mixed.

Table 3. Results grouped into 4 categories

Region	Category	Test phase Instances	Accuracy SVM	Ratio SVM	Ratio Logit
EUR	Budget	2,000	1,623	0.81	0.90
	Mid-low range	2,000	1,716	0.86	0.92
	Mid-high range	2,000	1,196	0.60	0.54
	Superior	2,000	1,724	0.86	0.80
AME	Budget	1,500	1,113	0.74	0.46
	Mid-low range	2,000	1,642	0.82	0.89
	Mid-high range	2,000	1,095	0.55	0.52
	Superior	2,000	1,658	0.83	0.78
ASP	Budget	2,000	1,660	0.83	0.94
	Mid-low range	2,000	1,657	0.83	0.90
	Mid-high range	2,000	1,092	0.83	0.50

	Superior	2,000	1,686	0.84	0.80
MEA	Budget	400	110	0.28	0.03
	Mid-low range	400	308	0.77	0.17
	Mid-high range	400	346	0.87	0.19
	Superior	400	355	0.89	0.14

Although in some categories of some regions the ordered logistic model predicts a bit better the category than SVM, the SVM results are more regular worldwide and, in general, show a better accuracy.

The SVM results show that around 80% predicts the accommodation category (divided into budget, mid-low range, mid-high range, and superior category) that a property could have by just knowing the price, the number of reviews, the ratings awarded by past users for location, cleanliness and value, and the number of people that have saved the property in their wish list.

The greatest accuracy of the SVM model is in the superior and the mid-high range categories in MEA. The accuracy in ASP is very high in all categories. In EUR and AME, the lowest accuracy is in the mid-high range category (3- to 4-star) with 60% and 55%, respectively. The worst prediction is found in MEA in the budget category, probably due to the fact that the parameters do not capture the difference in this range, as shown in Table 3.

In order to determine the importance of the features when classifying, LIBSVM proposes a method based on F-scores (Chen and Lin, 2006). For a given feature, its F-score is computed as the ratio of the discrimination between the positive and negative sets, over the particular value of the feature within each of the two sets. The larger the F-score is, the more likely this feature will be more discriminative, it being useful as a feature selection criterion. Even though the F-score does not reveal mutual information among features, it is a simple and efficient method.

Table 4. F-scores

Features	EUR	AME	ASP	MEA
Cleanliness	0.44	0.63	0.35	0.63
Value	0.05	0.12	0.03	0.19
Location	0.14	0.35	0.10	0.37
Listsaved	0.02	0.02	0.06	0.04
Reviews	0.06	0.01	0.07	0.08
Price	1.35	1.41	1.45	1.23

Table 4 shows that price is the most important feature when classifying, followed by cleanliness, and in AME and MEA, the location is also important; the other factors serve to explain the model but the significance is considerably lower. In this respect, the classification model based on the features of price, cleanliness and location is also well-suited to P2P accommodation platforms, which are engagement platforms intrinsically bound to UGC. Price is a key issue for P2P guests' choice and satisfaction (Wang and Nicolau, 2017), and cleanliness and location are among the most frequently mentioned topics – and in a similar order – in both P2P and hotel guests' UGC (Belarmino et al., 2017).

An ordered logistic regression was also performed to see if better results could be obtained, but the accuracy was generally worse when compared to the SVM results; the worst results were in MEA, where a maximum accuracy of 17% in 5-star hotels was obtained because there were fewer instances to predict the category than in the other regions.

To check the validity of the model in Airbnb properties, a small random sample of two cities was downloaded manually. The results show that properties were distributed between all categories (Table 5) and not solely among the top of the classification, something that might have been expected given that Airbnb properties' ratings tend to have a high positive skew and that it is rare to find a property with a lower than 3.5 rating (Zervas et al., 2015).

Table 5. Percentage of properties in Airbnb by four categories

Category	Subsample Airbnb
Budget	29.73%
Mid-low range	21.62%
Mid-high range	27.03%
Superior	21.62%

5. Discussion

Although there are differences among countries and even among regions within the same country, and while there are some systems that group hotel categories into fewer than 5 levels (e.g. Malta from 2- to 5-star), we can affirm that the hotel classification system can be inferred in general through other criteria and standards that have nothing to do with the official criteria assigned by regulations of public and non-public organisations.

Attempts to launch a process of harmonisation of the different regulations (Arcarons i Simon et al., 2008) to enable the unification of criteria for allocating stars in different countries (Hotrec, 2015) could be made by taking into account the User-Generated Content translated into ratings along with other factors such as price or score, because the results of this study show that it can be predicted with great accuracy worldwide, thereby avoiding criteria that could become out-dated with the passage of time (Torres et al., 2014). Such allocation of stars could also help users by reducing the problem of UGC information overload and by making P2P accommodation classification more comprehensive and simple.

The greatest accuracy is in 5-star hotels worldwide because it "is the only category that has a certain uniformity from an international point of view" (Minazzi 2010: 80). The accuracy of the remaining categories is fairly high, except the 1-star category in EUR, AME, and ASP, and the 2-star category in MEA. This may be because customers of 1- and 2-star hotels use ratings systems less often than those staying in 3- to 5-star hotels in the United Kingdom (Callan, 1995). It may also be because user satisfaction coincides with the hotel category in nine European countries, except for 1- and 2-star hotels, where there are no significant differences in seven countries (Austria, Germany, Greece, Italy, Poland, Portugal and Spain) (in press).

With the results grouped into 4 categories, the lowest accuracy is in the mid-high range category (3- to 4-star) in EUR and AME because hotel supply in that category varies from country to country (Minazzi, 2010).

The results confirm that price is the most important characteristic for inferring the hotel category, which is consistent with the idea that the hotel classification system is a regular forecaster of prices (Israeli, 2002), and that room prices have a very strong direct linear relationship with hotel categories (Martin-Fuentes, 2016). In this respect, it is worth mentioning that price could also be considered a good predictor in the case of P2P accommodation, as market rules would prevent the system from being tricked through prices (e.g., if a price does not correspond to what is being offered, customers would not buy it or would create negative reviews about it, resulting in reputation loss). This prevention would be stronger in the case of P2P platforms as their success is attributed to their wide range of prices (Wang and Nicolau, 2017) suited to different offerings.

Although charging higher prices might seem to be a way of achieving a higher rating, this is something that would not happen, at least in the short run, because, Airbnb or any other P2P accommodation platform should only classify a property if there are at least 5 reviews, which is what Booking.com does.

The next important feature for inferring the star category is cleanliness, which is also consistent with other studies that confirm cleanliness is a factor that strongly affects travellers' choices (Atkinson, 1988) and is a relevant feature to the hotel users' satisfaction (Barreda and Bilgihan, 2013; Choi and Chu, 2001), although it is not a determinant of hotel room price (Zhang et al., 2011). This variable had previously been identified as fundamental to P2P accommodation travellers' choices and satisfaction, as expressed in their online UGC (Belarmino et al., 2017; Tussyadiah and Zach, 2017).

Location, especially in AME and MEA, is also important for predicting the star category, which is a variable that has a significant effect on price (Saló et al., 2014; de Oliveira Santos 2016) and is a feature that cannot be changed or improved once the property has been built (Xie et al., 2014). This variable has been identified as key for P2P accommodation guests through UGC analysis (Belarmino et al., 2017; Tussyadiah and Zach, 2017).

The application of the model to a sample of Airbnb properties demonstrates the validity and applicability of the model for P2P accommodation platforms. Remarkably, this model brings together most of the factors identified by Varma et al., (2016) that Airbnb users and non-users employ when choosing accommodation, such as price, location, past experiences and reputation, and classify them into categories that are understandable worldwide.

In this respect, trust can generate positive outcomes by reducing transaction risks (Ba and Pavlou, 2002). It is vital for organisations like Airbnb, which is vulnerable to bad press

(Guttentag, 2015), and it is the main concern for Consumer-Generated Media organisations (Filieri et al., 2015) or for websites where UGC creates more confidence than communications from a company do (Gretzel and Yoo, 2008; Vermeulen and Seegers, 2009). Consequently, our model can give consumers of Airbnb or any other P2P accommodation platform additional confidence because the grading scheme categories in the hospitality sector are useful when it comes to mitigating asymmetric information (Martin-Fuentes 2016; Nicolau and Sellers 2010; Núñez-Serrano et al., 2014).

In addition, this model helps to provide customers with holistic information, which might make them feel they can rely more on Airbnb, and presents a comprehensive classification that may help users deal with the huge amounts of information available online. In a synthetic way, the aforementioned classification combines a well-known hotel-like classification system with UGC, and it is especially useful for users' faced with information fragmentation and overload. Moreover, a strength of the model is that it is partially based on UGC, along with other relevant factors, which consumers find highly trustworthy and is therefore consistent with the philosophy of P2P platforms as online engagement platforms, based on user interaction, UGC exchange and value co-creation.

Airbnb is trying to put measures in place to encourage service providers to become engaged in quality certifications like the 'Superhost' badge, which might seem as though it is offering a new classification system. However, such certifications have limited scope because a very low percentage of properties has the 'Superhost' badge (Liang et al., 2017), thus restricting the number of options available to users. The distinctive trait of our model is that all properties with at least five reviews will have a star assigned to them.

Unlike Airbnb ratings, which are mostly positive, this model classifies properties into all categories, which provides the user with more information because high star-ratings alone "are likely not informative enough for users to make informed consumer choice" (Bridges and Vásquez, 2016: 16).

Finally, this model will give more visibility to Airbnb for non-users who seem to be unaware of the existence of this alternative (Varma et al., 2016). It may also be used as a tool for comparing different types of accommodation in a given destination because most travellers use Airbnb to find alternatives to hotels. It is worth noting that only 2.3% of respondents indicated that without Airbnb they would not have taken the trip (Guttentag and Smith, 2017).

6. Conclusions

The rapid growth of the sharing economy, especially in the tourism sector, can be hampered by trust issues, as most business relationships will be customer-to-customer (C2C). To provide a measure of trust, several methods are being used: customer reviews, reputation-based systems, sharing on social media and so on. But, for those situations where prospective customers or others within their social networks do not have previous experience, a classification system is required to avoid opportunistic behaviours due to asymmetric information. Moreover, an integrative and synthetic classification is necessary, on the one hand, to prevent the information overload that tourists experience online and, on the other, to assist tourists in their decision-making processes. Such systems are in place for hotels, namely the star-rating system, but they are not implementable for sharing economy sites, as they would require too many resources and too much effort to work: inspections, bureaucracy, etc. Our system would overcome these limitations because it is not resource hungry; it only requires affordable computational resources. Besides, as the proposed system is partly based on UGC, it would also be useful for ensuring that hosts put every effort into offering a faultless service to get the best online reviews from users, thereby managing to reach the highest category.

The proposed system is not only useful for classifying P2P accommodation and overcoming trust issues in P2P platforms, but also represents an improvement for the entire hotel classification system. The current official system for assigning hotel categories creates many differences within the same category since stars do not mean the same worldwide. Many hotel category classifications work with a system of points that lets hotels organise themselves as they wish, meeting certain minimum requirements, but the same category has many differences. Besides, a classification system that includes guests' reviews is a proposal by the United Nations World Tourism Organization (Blomberg-Nygard and Anderson 2016: 26), principally because consumers use reviews and hotel classifications in different ways: "classification systems help filter hotels, whereas guest reviews provide a means to help select from a smaller set of acceptable options. These similar yet distinct uses indicate a continued need for both hotel classification and guest reviews." Our proposed system goes a step further since it combines reviews with a new classification system for hotels and P2P accommodation platforms in order to help simplify users' decision-making.

In this respect, our model would therefore provide several advantages:

1. Matching users' point of view: Experts deciding which criteria should be applied to officially allocate hotel categories should know that the ideal classification system is the one adapted to the users' needs, which takes into account that satisfaction might be obtained through eWOM.
2. Converging different systems: To standardise and bring in line the criteria used in different countries and regions in order to help users understand what each hotel category stand for.
3. Validating the official classification system: Audits would not need to be carried out to check that the criteria applied are being met, thus eliminating bureaucracy.

In short, the implementation of this model would achieve a reorientation of hotel classification systems to improve them, thereby bringing different countries, regions and systems in line and matching the systems to the users' opinions. This model contributes to the literature by determining which elements are more significant for inferring international hotel categories, bearing in mind that the system of hotel classification is not unified (each country and region applies its own regulations). Furthermore, as these elements are also available in P2P accommodation platforms, they can be used to create a model of accommodation categories equivalent to the hotel grading scheme, thus achieving a unified, comprehensive and real-time accommodation classification model based on online data.

6.1. Practical implications and limitations

This work could be used by adapting the classification model to other P2P platforms, in addition to Airbnb, such as Couchsurfing and home exchanges, or even to tourist attractions, based on data from travel opinion websites like TripAdvisor. This model could even be used for managing and consolidating online reputation through websites like Traity, with information coming from more than one platform (i.e., a property that is on HomeAway, Airbnb and Couchsurfing) and by combining this information. The application of this model implies in practice that accommodation categories are constantly updated through computerised systems based on available online information, representing a time- and cost-saving option.

The application of the proposed model has one disadvantage; properties that have only just been listed and do not have any reviews by previous users. They would start without any prior classification, but this is the same as currently happens when a user has to rely on a host that does not have a reference because he has not yet received an online travel review. On the positive side, once hosts achieve a category within the proposed model, it will prevent them from quitting their online identity if they have negative reviews (Ba and Pavlou, 2002), since the cost of getting a new online identity would involve the loss of the qualifying category. Such a cost might therefore be higher than trying to reverse the situation by improving the service offered to guests. Moreover, even if price (as set by the host) is part of the classification system, market rules and the inclusion of users' reviews would prevent hosts from setting higher prices to achieve higher categories than would otherwise correspond the characteristics of their offerings.
Similarly, to prevent the system from being manipulated through the use of price change strategies to achieve either a higher or a lower category, a moving price average for a given number of days or months in the past could be used in the model, or, even, instead of assigning categories on a particular date, it could be done online instantly, i.e., every time a user visits the accommodation information. By doing so, the price reflected would be the real price and any manipulation of the system could be mitigated.

Like any other research, the research presented here is not exempt from limitations. The proposal is made using data obtained from Booking.com, which, despite being a very popular website, is not the only one in existence. The results could be different if data from other websites like Ctrip, HolidayCheck, or TripAdvisor were used. Indeed, replicating the study using other data is a challenge for further research.

Finally, this research has been done using a large volume of data downloaded automatically from Booking.com and has explored the capacity of big data in the hospitality field, as suggested by Xiang et al. (2015).

Acknowledgements
This work was partially funded by the Spanish Ministry of the Economy and Competitiveness: research project TIN2015-71799-C2-2-P and ENE2015-64117-C5-1-R.
This research article has received a grant for its linguistic revision from the Language Institute of the University of Lleida (2017 call).

7. References

Abrate, G., Capriello, A., Fraquelli, G., 2011. When quality signals talk: Evidence from the Turin hotel industry. Tour. Manag. 32, 912–921. doi:10.1016/j.tourman.2010.08.006

Airbnb, 2016a. Airbnb [WWW Document]. URL http://www.airbnb.com (accessed 11.9.16).

Airbnb, 2016b. Airbnb [WWW Document]. URL https://www.airbnb.co.uk/help/article/4/how-does-airbnb-help-build-trust-between-hosts-and-guests (accessed 12.20.16).

Akerlof, G.A., 1970. The Market for“ Lemons”: Quality Uncertainty and the Market Mechanism. Q. J. Econ. 84, 488–500.

Akin, M., 2015. A novel approach to model selection in tourism demand modeling. Tour. Manag. 48, 64–72. doi:10.1016/j.tourman.2014.11.004

Arcarons i Simon, R., Goitia Serra, V., González Aznar, N., 2008. La clasificación hotelera en la Unión Europea: Un mercado poco común. Pap. Tur. 49–67.

Atkinson, A., 1988. Answering the eternal question: what does the customer want? Cornell Hotel Restaur. Adm. Q. 29, 12–13.

Ayeh, J.K., Au, N., Law, R., 2013. "Do We Believe in TripAdvisor?" Examining Credibility Perceptions and Online Travelers' Attitude toward Using User-Generated Content. J. Travel Res. 52, 437–452. doi:10.1177/0047287512475217

Ba, S.L., Pavlou, P.A., 2002. Evidence of the effects of trust building technology in electronic markets: Price, premiums and buyer behaviors. MIS Q. 26, 243–268. doi:10.2307/4132332

Banerjee, S., Chua, A.Y.K., 2016. In search of patterns among travellers' hotel ratings in TripAdvisor. Tour. Manag. 53, 125–131. doi:10.1016/j.tourman.2015.09.020

Barreda, A., Bilgihan, A., 2013. An analysis of user-generated content for hotel experiences. J. Hosp. Tour. Technol. 4, 263–280. doi:10.1108/JHTT-01-2013-0001

Belarmino, A., Whalen, E., Koh, Y., Bowen, J.T., 2017. Comparing guests' key attributes of peer-to-peer accommodations and hotels: mixed-methods approach. Curr. Issues Tour. 1–7. doi:10.1080/13683500.2017.1293623

Blomberg-Nygard, A., Anderson, C.K., 2016. United Nations World Tourism Organization study on online guest reviews and hotel classification systems: An integrated approach. Serv. Sci. 8, 139–151. doi:10.1287/s erv.2016.0139

Booking.com, 2016. About Booking.com [WWW Document]. URL http://www.booking.com/content/about.en-gb.html (accessed 9.23.16).

Botsman, R., Rogers, R., 2011. What's mine is yours: how collaborative consumption is changing the way we live. Collins London.

Breidbach, C.F., Brodie, R.J., 2017. Engagement platforms in the sharing economy: conceptual foundations and research directions. J. Serv. Theory Pract. 27.

Bridges, J., Vásquez, C., 2016. If nearly all Airbnb reviews are positive, does that make them meaningless? Curr. Issues Tour. 1–19. doi:10.1080/13683500.2016.1267113

Buczynski, B., 2013. Sharing is good: How to save money, time and resources through collaborative consumption. New Society Publishers.

Bulchand Gidumal, J., Melián González, S., 2016. Una guía para entender la economía colaborativa.

Byers, J., Proserpio, D., Zervas, G., 2013. The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry. SSRN Electron. J. (June 9, 2. doi:10.2139/ssrn.2366898

Callan, R.J., 1998. Attributional Analysis of Customers' Hotel Selection Criteria by U.K. Grading Scheme Categories. J. Travel Res. 36, 20–34. doi:10.1177/004728759803600303

Callan, R.J., 1995. Hotel classification and grading schemes, a paradigm of utilisation and user characteristics. Int. J. Hosp. Manag. 14, 271–283.

Cezar, A., Ögüt, H., 2016. Analyzing conversion rates in online hotel booking. Int. J. Contemp. Hosp. Manag. 28, 286–304. doi:10.1108/IJCHM-05-2014-0249

Chen, Y.-W., Lin, C.-J., 2006. Combining SVMs with various feature selection strategies, in: Feature Extraction. Springer, pp. 315–324.

Cheng, M., 2016. Sharing economy: A review and agenda for future research. Int. J. Hosp. Manag. 57, 60–70. doi:10.1016/j.ijhm.2016.06.003

Choi, T.Y., Chu, R., 2001. Determinants of hotel guests' satisfaction and repeat patronage in the Hong Kong hotel industry. Int. J. Hosp. Manag. 20, 277–297. doi:10.1016/S0278-4319(01)00006-8

Clerides, S., Nearchou, P., Pashardes, P., 2005. Intermediaries as bundlers, traders and quality assessors: the case of UK tour operators.

De Ascaniis, S., Gretzel, U., 2012. What's in a review title?, in: Fuchs, M., Ricci, F., Cantoni, L. (Eds.), Information and Communication Technologies in Tourism. Springer, New York, NY, pp. 460–470.

de Oliveira Santos, G.E., 2016. Worldwide hedonic prices of subjective characteristics of hostels. Tour. Manag. 52, 451–454. doi:10.1016/j.tourman.2015.07.001

Dellarocas, C., 2003. The digitization of word of mouth: Promise and challenges of online feedback mechanisms. Manage. Sci. 49, 1407–1424.

Dioko, L.A.N., So, S.-I. (Amy), Harrill, R., 2013. Hotel category switching behavior—Evidence of mobility, stasis or loyalty. Int. J. Hosp. Manag. 34, 234–244. doi:10.1016/j.ijhm.2013.04.002

Ert, E., Fleischer, A., Magen, N., 2016. Trust and reputation in the sharing economy: The role of personal photos in Airbnb. Tour. Manag. 55, 62–73. doi:10.1016/j.tourman.2016.01.013

Fang, B., Ye, Q., Kucukusta, D., Law, R., 2016. Analysis of the perceived value of online tourism reviews: Influence of readability and reviewer characteristics. Tour. Manag. 52, 498–506. doi:10.1016/j.tourman.2015.07.018

Fernández-Barcala, M., González-Díaz, M., Prieto-Rodríguez, J., 2010. Hotel quality appraisal on the Internet: a market for lemons? Tour. Econ. 16, 345–360. doi:10.5367/000000010791305635

Filieri, R., Alguezaui, S., McLeay, F., 2015. Why do travelers trust TripAdvisor? Antecedents of trust towards consumer-generated media and its influence on recommendation adoption and word of mouth. Tour. Manag. 51, 174–185. doi:10.1016/j.tourman.2015.05.007

Gretzel, U., Yoo, K.H., 2008. Use and Impact of Online Travel Reviews, in: O'Connor, P., Höpken, W., Gretzel, U. (Eds.), Information and Communication Technologies in Tourism. Springer Vienna, Vienna, pp. 35–46. doi:10.1007/978-3-211-77280-5_4

Guttentag, D., 2015. Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector. Curr. Issues Tour. 18, 1192–1217. doi:10.1080/13683500.2013.827159

Guttentag, D.A., Smith, S.L.J., 2017. Assessing Airbnb as a disruptive innovation relative to hotels: Substitution and comparative performance expectations. Int. J. Hosp. Manag. 64, 1–10. doi:10.1016/j.ijhm.2017.02.003

Harford, T., 2010. The undercover economist. Hachette UK.

Harrington, R., 2015. Vacation rentals: Commercial activity butting heads with CC&Rs. Calif. West. Law Rev. 51, 187–224.

Hensel, K., Deis, M.H., 2010. Using social media to increase advertising and improve marketing. Entrep. Exec. 15, 87–98.

Hotrec, 2015. Hotrec [WWW Document]. Hotel. Union polished criteria its Hotel. Categ. URL http://www.hotrec.eu/newsroom/press-releases-1714/hotelstars-union-polished-the-criteria-for-its-hotelstars-categories.aspx

Hsu, C.-W., Chang, C.-C., Lin, C.-J., 2003. A practical guide to support vector classification.

Hsu, C.-W., Lin, C.-J., 2002. A comparison of methods for multiclass support vector machines. IEEE Trans. Neural Networks 13, 415–425.

Israeli, A.A., 2002. Star rating and corporate affiliation: their influence on room price and performance of hotels in Israel. Int. J. Hosp. Manag. 21, 405–424. doi:10.1016/S0278-4319(02)00037-3

Jeacle, I., Carter, C., 2011. In TripAdvisor we trust: Rankings, calculative regimes and abstract systems. Accounting, Organ. Soc. 36, 293–309. doi:10.1016/j.aos.2011.04.002

Kim, M.-J., Chung, N., Lee, C.-K., 2011. The effect of perceived trust on electronic commerce: Shopping online for tourism products and services in South Korea. Tour. Manag. 32, 256–265. doi:10.1016/j.tourman.2010.01.011

Liang, S., Schuckert, M., Law, R., Chen, C.-C., 2017. Be a “Superhost”: The importance of badge systems for peer-to-peer rental accommodations. Tour. Manag. 60, 454–465.

Marine-Roig, E., 2017. Online travel reviews: A massive paratextual analysis, in: Xiang, Z., Fesenmaier, D.R. (Eds.), Analytics in Smart Tourism Design: Concepts and Methods. Springer, Heidelberg, Germany, pp. 179–202. doi:10.1007/978-3-319-44263-1_11

Martin-Fuentes, E., 2016. Are guests of the same opinion as the hotel star-rate classification system? J. Hosp. Tour. Manag. 29, 126–134. doi:10.1016/j.jhtm.2016.06.006

Martin-Fuentes, E., Fernandez, C., Mateu, C., 2016. Las estrellas muestran el camino: coincidencia entre satisfacción y categoría hotelera, in: Universidad de Malaga (Ed.), ICT & Tourism International Conference TURITEC. Malaga.

Minazzi, R., 2010. Hotel classification systems: a comparison of international case studies. Acta Univ. Danubius. Œconomica 6, 64–86.

Möhlmann, M., 2015. Collaborative consumption: determinants of satisfaction and the likelihood of using a sharing economy option again. J. Consum. Behav. 14, 193–207. doi:10.1002/cb.1512

Neirotti, P., Raguseo, E., Paolucci, E., 2016. Are customers’ reviews creating value in the hospitality industry? Exploring the moderating effects of market positioning. Int. J. Inf. Manage. 36, 1133–1143. doi:10.1016/j.ijinfomgt.2016.02.010

Nicolau, J.L., Sellers, R., 2010. The quality of quality awards: Diminishing information asymmetries in a hotel chain. J. Bus. Res. 63, 832–839. doi:10.1016/j.jbusres.2009.06.009

Núñez-Serrano, J.A., Turrión, J., Velázquez, F.J., 2014. Are stars a good indicator of hotel quality? Assymetric information and regulatory heterogeneity in Spain. Tour. Manag. 42, 77–87. doi:10.1016/j.tourman.2013.10.004

O'Connor, P., 2010. Managing a hotel's image on TripAdvisor. J. Hosp. Mark. Manag. 19, 754–772. doi:10.1080/19368623.2010.508007

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, 197–214. doi:10.1080/02642069.2010.529436

Park, S., Nicolau, J.L., 2015. Asymmetric effects of online consumer reviews. Ann. Tour. Res. 50, 67–83. doi:10.1016/j.annals.2014.10.007

Pirolli, B., 2016. Travel information online: navigating correspondents, consensus, and conversation. Curr. Issues Tour. 1–7. doi:10.1080/13683500.2016.1273883

Rifkin, J., 2000. The age of access: The new culture of hypercapitalism. Where All Life is a Paid. Exp. Tarcher, New York 33, 40–51.

Saló, A., Garriga, A., Rigall-I-Torrent, R., Vila, M., Fluvià, M., 2014. Do implicit prices for hotels and second homes show differences in tourists' valuation for public attributes for each type of accommodation facility? Int. J. Hosp. Manag. 36, 120–129. doi:10.1016/j.ijhm.2013.08.011

Schuckert, M., Liu, X., Law, R., 2015. Hospitality and Tourism Online Reviews: Recent Trends and Future Directions. J. Travel Tour. Mark. 32, 608–621. doi:10.1080/10548408.2014.933154

Sigala, M., 2015. Collaborative commerce in tourism: implications for research and industry. Curr. Issues Tour. 1–10. doi:10.1080/13683500.2014.982522

Stiglitz, J.E., 2002. Information and the Change in the Paradigm in Economics. Am. Econ. Rev. 92, 460–501.

Sun, S., Fong, L.H.N., Law, R., Luk, C., 2015. An Investigation of Gen-Y's Online Hotel Information Search: The Case of Hong Kong. Asia Pacific J. Tour. Res. 1–14. doi:10.1080/10941665.2015.1062405

Torres, E.N., Adler, H., Behnke, C., 2014. Stars, diamonds, and other shiny things: The use of expert and consumer feedback in the hotel industry. J. Hosp. Tour. Manag. 21, 34–43. doi:10.1016/j.jhtm.2014.04.001

Tussyadiah, I.P., Pesonen, J., 2016. Impacts of Peer-to-Peer Accommodation Use on Travel Patterns. J. Travel Res. 55, 1022–1040.

Tussyadiah, I.P., Pesonen, J., 2016. Drivers and barriers of peer-to-peer accommodation stay – an exploratory study with American and Finnish travellers. Curr. Issues Tour. 1–18. doi:10.1080/13683500.2016.1141180

Tussyadiah, I.P., Zach, F., 2017. Identifying salient attributes of peer-to-peer accommodation experience. J. Travel Tour. Mark. 34, 636–652. doi:10.1080/10548408.2016.1209153

Vapnik, V. (2013). *The nature of statistical learning theory*. Springer science & business media. (2nd ed. reprinted by Springer-Verlag 2000, 1995 New York, Inc.).

Varma, A., Jukic, N., Pestek, A., Shultz, C.J., Nestorov, S., 2016. Airbnb: Exciting innovation or passing fad? Tour. Manag. Perspect. 20, 228–237. doi:10.1016/j.tmp.2016.09.002

Vermeulen, I.E., Seegers, D., 2009. Tried and tested: The impact of online hotel reviews on consumer consideration. Tour. Manag. 30, 123–127. doi:10.1016/j.tourman.2008.04.008

Wang, D., Nicolau, J.L., 2017. Price determinants of sharing economy based accommodation rental: A study of listings from 33 cities on Airbnb.com. Int. J. Hosp. Manag. 62, 120–131. doi:10.1016/j.ijhm.2016.12.007

Xiang, Z., Schwartz, Z., Gerdes, J.H., Uysal, M., 2015. What can big data and text analytics tell us about hotel guest experience and satisfaction? Int. J. Hosp. Manag. 44, 120–130.

Xie, K.L., Zhang, Z., Zhang, Z., 2014. The business value of online consumer reviews and management response to hotel performance. Int. J. Hosp. Manag. 43, 1–12. doi:10.1016/j.ijhm.2014.07.007

Zervas, G., Proserpio, D., Byers, J., 2015. A First Look at Online Reputation on Airbnb, Where Every Stay is Above Average. Where Every Stay is Above Aver. (January 23, 2015).

Zhan-Qing, L., Liu, J.C., 1993. Assessment of the hotel rating system in China. Tour. Manag. 14, 440–452.

Zhang, Z., Ye, Q., Law, R., 2011. Determinants of hotel room price. Int. J. Contemp. Hosp. Manag. 23, 972–981. doi:10.1108/09596111111167551

Zheng, W., Ye, Q., 2009. Sentiment classification of Chinese traveler reviews by support vector machine algorithm, in: Intelligent Information Technology Application, 2009. IITA 2009. Third International Symposium on. IEEE, pp. 335–338.

9. Discussion, general conclusions and future work

This thesis makes several notable contributions to the field of UGC in the lodging industry.

9.1. Discussion and conclusions

The general conclusion of this thesis is that UGC from the most popular tourism platforms, either from community-based site that users can post a review to without being verified or from the transaction-based OTA with verified guests, validates the grading schemes of the lodging industry.

This validation enables the creation of an international classification system that could categorize any type of accommodation (hotels, apartments, private properties, etc.) so that they can be compared using the same classifier. The system could also be used to classify any other product or service that could potentially be classified by UGC.

In this regard, five UGC-based articles have been published, all of which drew on big data; more than 18 million online reviews of hotels worldwide from Booking.com and more than 11 million from TripAdvisor were downloaded and analyzed in this research. The results would have been impossible to obtain by means of survey-based studies and this thesis provides an international vision of the accommodation sector and the accommodation classification system that, to the author's knowledge at the time of writing, is unlike published studies that have focused solely on the analysis of cities, countries or regions, but not the whole world.

In particular, from the first article entitled "Does verifying users influence rankings? Analyzing TripAdvisor and Booking.com", it can be concluded that hotel rankings worldwide have a high degree of relationship between the rankings on Booking.com and on TripAdvisor, thus showing that the possible publication of fake reviews on TripAdvisor (because users of this website are not verified) does not seem to be prevalent, as the hotel position on both rankings behaves similarly. Suspicions of fraud to benefit or harm properties on TripAdvisor do not seem to affect hotels because the enormous amount of online reviews on this website seems to cushion the potentially negative effects of the possible fake reviews.

It is important to highlight that this finding contributes to the validation of UGC from TripAdvisor, despite the fact that contributors to this website are not verified, and to the validation of reviews from verified users on Booking.com. This finding is significant because it means that not only users and hotel managers can rely on these opinions, but so too can researchers, because this website is an important source of information for much research.

Moreover, and comparing the unique rating scale of Booking.com (from 2.5 to 10) to TripAdvisor's scale (from 1 to 5), the results confirm that Booking.com's scale is beneficial to low-quality hotels, especially those in America and Europe, and detrimental to high-quality hotels worldwide, which leads to the recommendation for hotel managers to take care when deciding which OTA is best for marketing their property, because the ranking and score results may differ depending on the measurement scale and the way guests' opinions are collected. Furthermore, users should know that the measurement scale can be beneficial or harmful to some hotels to avoid getting any unpleasant surprises when booking a hotel, because not all that glitters is gold.

The second article entitled "The more the merrier? Number of reviews versus score on TripAdvisor and Booking.com" confirms that there is a relationship between the amount of reviews and the score on TripAdvisor, called "volume", as other authors have previously suggested when analyzing different destinations in Europe (Melian-Gonzalez et al., 2013). However, the main contribution of this study is that neither does this tendency behave in the same way worldwide, nor do the scores on other platforms, such as Booking.com.

On Booking.com the number of reviews is not related to the score because this OTA removes reviews that are older than 24 months and it does not use those reviews to calculate the hotel's overall score. Instead, they keep them so that users can read them if they need to. Booking.com therefore shows the current reality of the properties and allows them to obtain scores that is closer to the actual situation.

In general, and as a practical implication, it would be expedient for the stakeholders that consult UGC, whether they are users before starting a trip or managers who want to know the guests' opinions of their business, to know how these platforms operate, what the measurement scale is, which parameters are taken into account to obtain a score or a position in the ranking, what the system for collecting reviews on those websites is, how they use old reviews, and so on. Even researchers in their studies should take these premises into account in to prevent confusion in their results, as exemplified by Mellinas et al. (2016) with regard to the unique measurement scale of Booking.com.

Encouraging guests to write reviews about their experiences on TripAdvisor would help hotels obtain not only better results, but also better positions in the ranking since the implementation of the new Popularity Ranking algorithm for Hotels in 2016 (TripAdvisor, 2016c), which takes into account the quantity, recency, and quality of reviews to obtain better positions. However, it is important to highlight that TripAdvisor does not allow hotels to reward travelers for writing reviews (TripAdvisor, 2013).

As stated by Striphas (2015), it is impossible to know what is "under the hood" at Amazon, Google, Facebook or any number of other leading tech firms such as TripAdvisor, and the algorithms are so decisive for these companies that they are becoming "the new apostles of culture". Thus, it is important for users to take into account that the TripAdvisor ranking is built on criteria that not only consider users' opinions, but also apply other factors decided by the company itself, as happens with other rankings where subjective criteria such as Michelin Stars for restaurants or the Robert Parker Wine List, the difference being that, in the latter two cases, users are aware of their subjectivity.

These conclusions close the first part of this thesis, in which UGC relating to the hotel sector posted on a recommendation system and on a sales platform is compared. The thesis continues with a comparative study of UGC on both platforms, and with a new part relating to hotel classification systems worldwide.

This part demonstrates that user-generated ratings coincides with room price and with the hotel category, which is an important finding considering that despite the differences in criteria in implementing the hotel category worldwide, where each country or even each region has its own regulations, a relationship does exist between the scores awarded by guests on both websites studied.

Moreover, it is confirmed that room prices are related to hotel categories and with users' scores, so those hotels with the highest room prices obtain a better position in the ranking of each website. Furthermore, the number of rooms does not influence the score awarded but, depending on the region, there is a relationship between hotel size and category. However, there is an exception when analyzing the categories in depth because, in some countries, guests do not perceive significant differences between 1-star and 2-star hotels, according to their ratings.

Thus, it is concluded that the hotel classification system conveniently fulfills its purpose, as both prices and customer ratings increase with each additional star. Hotel categories can be used as a tool to mitigate the possible adverse effects of information asymmetry and future guests can use the hotel categories as a filter in their choice of hotels according to their needs. Also, it is important to highlight that UGC allows a better positioning of each hotel.

Another implication that emerges from this research is that, after analyzing thousands of hotels, we found there were too many that did not have complete information relating to their hotel category on the two websites. Given the influence of these websites as a source of information for users before making a reservation, hoteliers should take care of the information provided about their properties and to complete or correct it if necessary.

In the last article entitled "Modelling a grading scheme for P2P accommodation: Stars for Airbnb", valuable conclusions are drawn about the fact that UGC is related to the hotel categories despite the regulations for assigning hotel categories being different in each country or even in each region.

In this respect, the hotel categories at an international level are predicted from data generated specially by users through their online travel reviews and from other features. The methodology used to predict the hotel categories was machine learning, specifically with the use of SVMs as a classifier. This technique has hardly been used in the tourism and hospitality field yet the results are very accurate. This methodology is recommended for improving the predictive power of tourism demand from UGC big data (Miah et al., 2017) and, as in this research, the results have proven to be better than when other traditional techniques such as logistic regression are used.

This finding could help the initiative carried out by the Association of Hotels, Restaurants and Cafés in Europe to harmonize the criteria of the lodging industry by implementing a scoring system to bring the hotel categories in Europe closer to one another. Although this association has been in operation since 2004, only 17 countries were members of it at the time of writing.

In addition, this finding could help the accommodation industry to find a better fit between the hotel categories and the online travel reviews in order to integrate consumers' needs into a single system (Blomberg-Nygard & Anderson 2016).

If the experts responsible for deciding which criteria should be applied to officially assign the hotel categories agree with guests' needs, then that would be the right situation. However, if the experts believe that their ideal model is one that does not match consumers' aims, then there is a problem. In other words, the best model would be the one that fits the guests' needs, the model in which the categories are closer to what customers want and what users value.

As mentioned previously, it is especially relevant to apply these methods to the hospitality industry, not only to hotels or traditional properties, but also to the new online collaborative tourism platforms whose raison d'être lies within the collaborative web. These platforms base their operation and success on value co-creation, user interactions, information exchange and the production of UGC by different economic actors in a service ecosystem defined as "online engagement platforms" (Breidbach & Brodie, 2017).

This model does not include the tangible characteristics for assigning stars on P2P platforms but, as this research indeed demonstrates, the hotel category of most hotels worldwide can be inferred from UGC (ratings, number of reviews, number of wish lists, etc.) and from other parameters such as price, in such a way that criteria worldwide are unified to create new standards in tourism across nations in order to help increase transparency in decision-making for tourists, which is easily understood by all.

Moreover, the model does not use tangible characteristics because some regulations assign a better category depending on the fulfillment of some items that cannot be found in private properties, such as a staff elevator, parking for buses, direct communication service between the room and the reception, a separate reception desk for staff, and because such tangible elements must be audited from time to time by public or private institutions to check if the hotels still meet the requirements to keep or to improve their hotel star-rating, which is highly bureaucratic. Furthermore, if this model is to be used to compare different lodging properties within the same destination, whatever their type, it is not possible to include tangible elements that cannot be found in all properties.

Additionally, regulations worldwide are completely different and, for that reason, this model stands out from the traditional system because it can predict the hotel category worldwide with great accuracy, which would allow users to compare hotels (and any other types of accommodation that may decide to implement this model). The audits carried out to check if the category achieved corresponds exactly to the variables offered by the hotels would become redundant or be done only in those cases where there is a mismatch between the category and the results in our model. Such a mismatch could be resolved just by knowing about certain public features, most of which are related to UGC. Thus, the bureaucracy related to the hotel classification system could be dramatically reduced as the number of audits to check if the criteria are met to keep or to lose a star would be minimized or better targeted.

Apart from creating a model for the accommodation industry that is equivalent to the hotel grading scheme, this model also contributes to the literature by finding the most significant elements for inferring international hotel categories, which are price, cleanliness and location. These variables fit appropriately into P2P lodging platforms because, as other authors have confirmed (although the literature in this field is scarce), price is a key issue for the guests' choice of and satisfaction with these types of accommodation. Cleanliness and location are also among the most-mentioned topics on P2P platforms, as it is in hotel guests' UGC.

In addition, the inclusion of price in the model might suggest that there is potential to manipulate the model via price-change strategies. Although it does indeed exist, it would be hard to continue doing so. To implement such a strategy, either to increase or decrease the rating, prices would need to be changed for the model to give the host a higher or lower category. To be able to succeed in changing the rating, the classification for the host would have to be done on a fixed date, which is known to the host, taking the price on that date as the reference price. Thus, the host could change the price on that date to manipulate the model into giving him a different rating. To avoid this, one of several strategies (or a combination thereof) could be implemented. Firstly, for the price trick to work, the host must know the exact date when the rating is computed, any uncertainty on that would imply that the host would have to keep the fake price for longer periods, so, in fact, it would not be a fake price but the real offered price to guests. Another possibility is not to use a fixed-point-in-time price, but instead a moving average for the last n-months price (for n>6 months, for example, which also helps to reduce the effects of seasonality on price). By using this method, the same situation as the one explained above applies: the host would have to keep the fake price for longer periods of time, thus it is, in fact, the real price. The final possibility is to compute the ranking online, i.e., every time a guest checks the lodging. This makes it even harder for hosts to trick the system, because the price will always be the one offered.

It is worth noting that some analyses that excluded price from the features were carried out and the results are quite similar; the accuracy is not as great as it is when price is included in the model, but it does predict the hotel category.

Finally, the classification model is not intended to be Airbnb specific, but as platform agnostic as possible. Thus, the proposed classification model could serve either as a tool for making comparisons between hotels, Airbnb and other third-party lodging platforms, as a metasearch engine, that merges all the different lodging options in a given destination and provides a standard and well-known system for comparing them. Moreover, it could be used for any product or service that could potentially be classified and rated by users, or even to create a platform unifying businesses' digital reputation.

9.2. Future work

We are continuing to work on different lines of research related to UGC and eWOM in the hospitality industry.

The exponential growth of tourism-related and, in particular, accommodation-industry-related UGC enables researchers to obtain valuable information from social media through the huge quantity of data about guests' experiences and behaviors. In this respect, one of the lines of research on which work needs to be done is that of gaining more in-depth knowledge of the behavior of consumers who review tourism services on social media, especially through big data analytics of online travel reviews from TripAdvisor. The research questions to explore are related to the time it takes a user to make an assessment after the tourism product is consumed; the type of device used to post a review (mobile phones or personal computer) in order to know whether the valence is more negative or more positive since mobile phones allow more immediate evaluations to be made; the evaluation of experienced or inexperienced users to know whether they assess properties differently (better or worse); and the segmentation of reviewers by age, gender, language and traveler type in order to characterize the profile of evaluators on tourism- and travel-related social media.

Although this thesis concludes that possible fake reviews on TripAdvisor do not alter the position of hotels in the ranking compared with Booking.com, tourism, like any other industry, is not immune to malicious online reviews. The scarce literature about the negative side of value co-creation known as value co-destruction (VCD) (Plé & Chumpitaz-Caceres, 2010) has led us to start conducting research on detecting suspicious online travel reviews, distinguishing between authentic and fictitious reviews.

Related again to UGC, we are trying to analyze what effect TripAdvisor's insistent requests for businesses to generate more reviews in order to improve their scores and the position of hotels in the ranking. In this respect, we are trying to quantify which hotels obtain more reviews by their geographical location, by their size (number of rooms) and by the simple Review per Room (RpR) ratio. This ratio is also analyzed for Booking.com in order to establish the characteristics of hotels that are more dependent on this OTA. We would also like to analyze whether the change of algorithm on TripAdvisor, which takes into account quantity, recency, and quality, affects the ranking position of some hotels compared to others according to their size. In this respect, and taking into account that the number of rooms and the number of reviews on TripAdvisor and on Booking.com are correlated because more rooms can lodge more customers who can post more reviews, the new algorithm may be of concern to smaller properties. To know whether or not such concern is founded, a comparison of hotel data from two different periods before and after the application of the new algorithm would need to be done.

We are also working on trying to improve the grading scheme that predicts hotel categories by including new UGC-related variables, working again with big data and using machine learning techniques with a dual purpose: on the one hand to try to improve the model by including new features, and on the other, to establish the significance of the new features in order to infer lodging categories.

Lastly, and following the open line of research comparing traditional lodging establishments and the P2P accommodation platforms, we are going to analyze the impact of collaborative accommodation from different perspectives, especially by analyzing the pricing policy – in peak season and in low season – of both models to better understand the phenomenon of collaborative tourist accommodation.

10. Other research activities

10.1. Other publications

The author of this thesis has also participated in other research activities with other researchers. The following articles have been published and submitted during the doctoral program in different journals:

- Martin-Fuentes, E. & Mellinas, J.P. (2018). Hotels that most rely on Booking.com - online travel agencies (OTAs) and hotel distribution channels. *Tourism Review.* https://doi.org/10.1108/TR-12-2017-0201
- Mellinas, J.P. & Martin-Fuentes, E. (2018). Does hotel size matter to get more reviews per room? *Information Technology & Tourism* (accepted with minor changes).
- Marine-Roig, E. Martin-Fuentes, E., & Daries-Ramon, N. (2017). User-Generated Social Media Events in Tourism. *Sustainability*, *9*(12), 22-50.
- Cristobal-Fransi, E., Daries-Ramon, N., Mariné-Roig, E., & Martin-Fuentes, E. (2017). Implementation of Web 2.0 in the snow tourism industry: Analysis of the online presence and e-commerce of ski resorts. *Spanish Journal of Marketing-ESIC*, *21*(2), 117-130.
- Daries Ramón, N., Cristóbal Fransi, E., Martín Fuentes, E., & Mariné Roig, E. (2017). Desarrollo de las TIC en el turismo de nieve: Análisis de la presencia en línea de las estaciones de esquí de España y Andorra. *Documents d'Anàlisi Geogràfica, 2017, 63*(2), 399-426.
- Balagué, C., Martin-Fuentes, E., & Gómez, M. J. (2016). Fiabilidad de las críticas hoteleras autenticadas y no autenticadas: El caso de TripAdvisor y Booking.com. *Cuadernos de Turismo*, *38*, 67-86.
- Verdú-Surroca, N. & Martin-Fuentes, E. (2016). University students' interactions using scaffolds in two different virtual forums. *International Journal of Learning Technology*, *11*(2), 114-133.
- Daries-Ramon, N., Cristóbal-Fransi, E., Martin-Fuentes, E., & Marine-Roig, E. (2016). Adopción del comercio electrónico en el turismo de nieve y montaña: análisis de la presencia web de las estaciones de esquí a través del Modelo eMICA. *Cuadernos de Turismo*, *37*, 113-134.

10.2. Contributions to conferences

The author of this thesis has also contributed with the following conference papers:

- Marine-Roig, E. Martin-Fuentes, E., Cristóbal-Fransi, E., & Ferrer-Rosell, B. (2018). Differential Price Management in Hotels and Peer-to-Peer Accommodation. T-Forum - The Tourism Intelligence Forum. Palma de Mallorca (Spain), Emerging Scholar Award.

- Cristóbal-Fransi, E., Daries-Ramon, Martin-Fuentes, E., & Español, L. (2018) Adopción del comercio electrónico en el turismo industrial: análisis de la presencia web de los recursos turísticos industriales. *XXI Congreso Internacional de Turismo Universidad-Empresa de la Universidad Jaume I*. Castelló (Spain), Best Paper Award.
- Marine-Roig, E. Martin-Fuentes, E., & Daries-Ramon, N. (2017). Eventos generados por el usuario: Un nuevo fenómeno a tener en cuenta. Primer Congreso Internacional sobre Desarrollo Social y Territorial INDEST. Lleida (Spain).
- Martin-Fuentes, E., Fernandez, C., & Mateu, C. (2017). The right stars: Guessing the hotel category from unrelated features. *9th World Conference for Graduate Research in Tourism, Hospitality & Leisure*. Cartagena (Spain).
- Daries-Ramon, N., Pal, A., Martin-Fuentes, E., & Cristóbal-Fransi, E. Turismo accesible, una oportunidad de diferenciación para los destinos. *XX Congreso Internacional de Turismo Universidad-Empresa de la Universidad Jaume I*. Castelló (Spain).
- Martin-Fuentes, E., Fernandez, C., & Mateu, C. (2016). Las estrellas muestran el camino: coincidencia entre satisfacción y categoría hotelera. In Universidad de Malaga (Ed.), *ICT & Tourism International Conference TURITEC*. Málaga (Spain).
- Cristobal-Fransi, E., Daries-Ramon, N., Mariné-Roig, E., & Martin-Fuentes, E. (2016). Turismo de nieve 2.0: Presencia en Internet y grado de desarrollo del comercio electrónico en las estaciones de esquí de España y Andorra. XXVIII Congreso de Marketing (AEMARK). León (Spain).

10.3. Research stay abroad

During the elaboration of the thesis, the candidate did a three-month research stay (from 1 November 2015 to 31 January 2016) at the Escola Superior d'Hotelaria e Turismo do Estoril, Portugal, with Dr Jorge Umbelino.

10.4. Participation in projects

Participation in the following research projects during the doctoral program:

- Razonamiento, satisfacción y optimización: argumentación y problemas funded by the Spanish Ministry of Economy, Industry and Competitiveness. Project number: TIN2015-71799-C2-2-P.

- Tourism analysis of peer-to-peer accommodation platforms in Spanish destinations through user-generated content and other online sources funded by the Spanish Ministry of Economy, Industry and Competitiveness. Project number: ECO2017-88984-R.

11. References

Abrate, G., & Viglia, G. (2016). Strategic and tactical price decisions in hotel revenue management. *Tourism Management*, *55*, 123–132. https//doi.org/10.1016/j.tourman.2016.02.006

Abrate, G., Capriello, A., & Fraquelli, G. (2011). When quality signals talk: Evidence from the Turin hotel industry. *Tourism Management*, *32*(4), 912–921. https://doi.org/10.1016/j.tourman.2010.08.006

Airbnb. (2016a). Airbnb. Retrieved November 9, 2016, from http://www.airbnb.com

Airbnb. (2016b). Airbnb. Retrieved December 20, 2016, from https://www.airbnb.co.uk/help/article/4/how-does-airbnb-help-build-trust-between-hosts-and-guests

Akerlof, G. A. (1970). The Market for“ Lemons”: Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics*, *84*(3), 488–500. https://doi.org/10.1016/B978-0-12-214850-7.50022-X

Akin, M. (2015). A novel approach to model selection in tourism demand modeling. *Tourism Management*, *48*, 64–72. http://doi.org/10.1016/j.tourman.2014.11.004

Anderson, C. K. (2012). The Impact of Social Media on Lodging Performance. *Cornell Hospitality Report*, *12*(15), 4–11. Retrieved from http://www.budigitalhub.com/sites/default/files/white_papers/HotelsSocialMedia.pdf

Anderson, E. W. (1998). Customer Satisfaction and Word of Mouth. *Journal of Service Research*, *1*(1), 5–17. http://doi.org/10.1177/109467059800100102

Arcarons i Simon, R., Goitia Serra, V., & González Aznar, N. (2008). La clasificación hotelera en la Unión Europea: Un mercado poco común. *Papers de Turisme*, (43-44), 49–67.

Arndt, J. (1967). Role of product-related conversations in the diffusion of a new product. *Journal of Marketing Research*, 291–295. https://doi.org/10.2307/3149462

Atkinson, A., (1988). Answering the eternal question: what does the customer want? *The Cornell Hotel and Restaurant Administration Quarterly*, 29(2), 12–14. https://doi.org/10.1177/001088048802900209

Ayeh, J. K., Au, N., & Law, R. (2013). “Do We Believe in TripAdvisor?” Examining Credibility Perceptions and Online Travelers’ Attitude toward Using User-Generated Content. *Journal of Travel Research*, *52*, 437–452. doi:10.1177/0047287512475217

Ba, S. L., & Pavlou, P. A. (2002). Evidence of the effects of trust building technology in electronic markets: Price, premiums and buyer behaviors. *MIS Quarterly*, *26*(3), 243–268. http://doi.org/10.2307/4132332

Baka, V. (2016). The becoming of user-generated reviews: Looking at the past to understand the future of managing reputation in the travel sector. *Tourism Management*, *53*, 148–162. http://doi.org/10.1016/j.tourman.2015.09.004

Balagué, C., Martin-Fuentes, E., & Gómez, M. J. (2016). Fiabilidad de las críticas hoteleras autenticadas y no autenticadas: El caso de TripAdvisor y Booking.com. *Cuadernos de Turismo*, *38*, 67-86. http://dx.doi.org/10.6018/turismo.38.271351

Banerjee, S., & Chua, A. Y. K. (2016). In search of patterns among travellers’ hotel ratings in TripAdvisor. *Tourism Management*, *53*, 125–131. https://doi.org/10.1016/j.tourman.2015.09.020

Barreda, A., & Bilgihan, A. (2013). An analysis of user - generated content for hotel experiences. *Journal of Hospitality and Tourism Technology*, *4*(3), 263–280. https://doi.org/10.1108/JHTT-01-2013-0001

Baum, J. A. C., & Mezias, S. J. (1992). Localized competition and organizational failure in the Manhattan hotel industry, 1898-1990. *Administrative Science Quarterly*, 580–604. http://doi.org/10.2307/2393473

Belarmino, A., Whalen, E., Koh, Y., & Bowen, J. T. (2017). Comparing guests' key attributes of peer-to-peer accommodations and hotels: mixed-methods approach. *Current Issues in Tourism*, (in press), 1–7. http://doi.org/10.1080/13683500.2017.1293623

Ben Aissa, S., & Goaied, M. (2016). Determinants of Tunisian hotel profitability: The role of managerial efficiency. *Tourism Management*, *52*, 478–487. doi:10.1016/j.tourman.2015.07.015

Bjørkelund, E., Burnett, T. H., & Nørvåg, K. (2012). A study of opinion mining and visualization of hotel reviews. In *Proceedings of the 14th International Conference on Information Integration and Web-based Applications & Services - IIWAS '12* (p. 229). New York, New York, USA: ACM Press.

Blomberg-Nygard, A., & Anderson, C. K. (2016). United Nations World Tourism Organization study on online guest reviews and hotel classification systems: An integrated approach. *Service Science*, *8*(2), 139–151. http://doi.org/10.1287/s erv.2016.0139

Bold, B. (2012). Tripadvisor appoints Live Union for Asian expansion. *Conference & Incentive Travel*, 6. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=hjh&AN=74438411&lang=es &site=ehost-live&scope=site

Booking.com, (2016). About Booking.com. Retrieved September 23, 2016, from http://www.booking.com/content/about.en-gb.html

Booking.com. (2018). About Booking.com. Retrieved January 10, 2018, from http://www.booking.com

Botsman, R., & Rogers, R. (2011). *What's mine is yours: how collaborative consumption is changing the way we live*. Collins London.

Boyd, D. E., Clarke, T. B., & Spekman, R. E. (2014). The emergence and impact of consumer brand empowerment in online social networks: A proposed ontology. *Journal of Brand Management*, *21*(6), 516–531. http://doi.org/10.1057/bm.2014.20

Breidbach, C. F., & Brodie, R. J. (2017). Engagement platforms in the sharing economy: conceptual foundations and research directions. *Journal of Service Theory and Practice*, *27*(4). 761–777. https://doi.org/10.1108/JSTP-04-2016-0071

Bridges, J., & Vásquez, C. (2016). If nearly all Airbnb reviews are positive, does that make them meaningless? *Current Issues in Tourism*, 1–19. http://doi.org/10.1080/13683500.2016.1267113

Buczynski, B., 2013. Sharing is good: How to save money, time and resources through collaborative consumption, New Society Publishers.

Buhalis, D., & Law, R. (2008). Progress in information technology and tourism management: 20 years on and 10 years after the Internet - The state of eTourism research. *Tourism Management, 29*(4), 609-623. https://doi.org/10.1016/j.tourman.2008.01.005

Bulchand Gidumal, J., & Melián González, S. (2016). Una guía para entender la *economía colaborativa*. (J. Bulchand Gidumal & S. Melián González, Eds.).
Bulchand-Gidumal, J., Melián−González, S., & González López−Valcárcel, B. (2011). Improving hotel ratings by offering free Wi−Fi. *Journal of Hospitality and Tourism Technology*, *2*(3), 235–245. http://doi.org/10.1108/17579881111173776
Burton, J., & Khammash, M. (2010). Why do people read reviews posted on consumer-opinion portals? *Journal of Marketing Management*, *26*(3-4), 230–255. https://doi.org/10.1080/02672570903566268
Butler, R. W. (1980). The concept of a tourist area cycle of evolution: Implications for management of resources. *The Canadian Geographer/Le Géographe Canadien*, *24*(1), 5–12. https://doi.org/10.1111/j.1541-0064.1980.tb00970.x
Byers, J., Proserpio, D., & Zervas, G. (2013). The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry. *SSRN Electronic Journal*. http://doi.org/10.2139/ssrn.2366898
Callan, R. J. (1995). Hotel classification and grading schemes, a paradigm of utilisation and user characteristics. *International Journal of Hospitality Management*, *14*(3), 271–283. https://doi.org/10.1016/0278-4319(95)00030-5
Callan, R. J. (1998). Attributional Analysis of Customers' Hotel Selection Criteria by U.K. Grading Scheme Categories. *Journal of Travel Research*, *36*(3), 20–34. http://doi.org/10.1177/004728759803600303
Cantallops, A. S., & Salvi, F. (2014). New consumer behavior: A review of research on eWOM and hotels. *International Journal of Hospitality Management*, *36*, 41–51. https://doi.org/10.1016/j.ijhm.2013.08.007
Casaló, L. V., Flavián, C., Guinalíu, M., & Ekinci, Y. (2015). Do online hotel rating schemes influence booking behaviors? *International Journal of Hospitality Management*, *49*, 28–36. https://doi.org/10.1016/j.ijhm.2015.05.005
Cezar, A., & Ögüt, H. (2016). Analyzing conversion rates in online hotel booking. *International Journal of Contemporary Hospitality Management*, *28*(2), 286–304. http://doi.org/10.1108/IJCHM-05-2014-0249
Chaves, M. S., Gomes, R., & Pedron, C. (2012). Analysing reviews in the Web 2.0: Small and medium hotels in Portugal. *Tourism Management*, *33*(5), 1286–1287. http://doi.org/10.1016/j.tourman.2011.11.007
Chen, Y.-F., & Law, R. (2016). A Review of Research on Electronic Word-of-Mouth in Hospitality and Tourism Management. *International Journal of Hospitality & Tourism Administration*, *17*(4), 347–372. http://doi.org/10.1080/15256480.2016.1226150
Chen, Y.-W., & Lin, C.-J. (2006). Combining SVMs with various feature selection strategies. In *Feature extraction* (pp. 315–324). Springer.
Cheng, M. (2016). Sharing economy: A review and agenda for future research. *International Journal of Hospitality Management*, *57*, 60–70. http://doi.org/10.1016/j.ijhm.2016.06.003
Cheung, C. M. K., & Thadani, D. R. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. *Decision Support Systems*, *54*(1), 461–470. http://doi.org/10.1016/j.dss.2012.06.008
Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of marketing research*, *43*(3), 345–354. https://doi.org/10.1509/jmkr.43.3.345

Chitika. (2013). The Value of Google Result Positioning. Retrieved August 6, 2015, from https://chitika.com/google-positioning-value

Choi, T. Y., & Chu, R. (2001). Determinants of hotel guests' satisfaction and repeat patronage in the Hong Kong hotel industry. *International Journal of Hospitality Management*, *20*(3), 277–297. http://doi.org/10.1016/S0278-4319(01)00006-8

Chung, W., & Kalnins, A. (2001). Agglomeration effects and performance: A test of the Texas lodging industry. *Strategic Management Journal*, *22*(10), 969–988. https://doi.org/10.1002/smj.178

Claver−Cortés, E., Molina−Azorín, J. F., & Pereira−Moliner, J. (2007). The impact of strategic behaviours on hotel performance. *International Journal of Contemporary Hospitality Management*, *19*(1), 6–20. http://doi.org/10.1108/09596110710724125

Clerides, S., Nearchou, P., & Pashardes, P. (2005). Intermediaries as bundlers, traders and quality assessors: the case of UK tour operators. CEPR Discussion Paper No. 5038. Available at SSRN: https://ssrn.com/abstract=774165

Cohen, E. (1972). Toward a sociology of international tourism. *Social Research*, 164–182.

Cohen, J. (1988). Statistical power analysis for the behavioural sciences. Hillside. *NJ: Lawrence Earlbaum Associates, 2*.

Danziger, S., Israeli, A., & Bekerman, M. (2006). The relative role of strategic assets in determining customer perceptions of hotel room price. *International Journal of Hospitality Management*, *25*(1), 129–145. http://doi.org/10.1016/j.ijhm.2004.12.005

De Ascaniis, S., & Gretzel, U. (2012). What's in a review title? In M. Fuchs, F. Ricci, & L. Cantoni (Eds.), *Information and Communication Technologies in Tourism*, (pp. 460–470). New York, NY: Springer.

de Oliveira Santos, G. E. (2016). Worldwide hedonic prices of subjective characteristics of hostels. *Tourism Management*, *52*, 451–454. https://doi.org/10.1016/j.tourman.2015.07.001

Dellarocas, C. (2003). The digitization of word of mouth: Promise and challenges of online feedback mechanisms. *Management Science*, *49*(10), 1407–1424. https://doi.org/10.1287/mnsc.49.10.1407.17308

Dellarocas, C., Zhang, X. (Michael), & Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing*, *21*(4), 23–45. http://doi.org/10.1002/dir.20087

Denizci Guillet, B., & Law, R. (2010). Analyzing hotel star ratings on third-party distribution websites. *International Journal of Contemporary Hospitality Management*, *22*(6), 797–813. http://doi.org/10.1108/09596111011063098

Dioko, L. A. N., So, S.-I. (Amy), & Harrill, R. (2013). Hotel category switching behavior—Evidence of mobility, stasis or loyalty. *International Journal of Hospitality Management*, *34*, 234–244. https://doi.org/10.1016/j.ijhm.2013.04.002

Duan, W., Gu, B., & Whinston, A. B. (2008). The dynamics of online word-of-mouth and product sales—An empirical investigation of the movie industry. *Journal of Retailing*, *84*(2), 233–242. https://doi.org/10.1016/j.jretai.2008.04.005

Ert, E., Fleischer, A. & Magen, N. (2016). Trust and reputation in the sharing economy: The role of personal photos in Airbnb. *Tourism Management*, 55, 62–73. https://doi.org/10.1016/j.tourman.2016.01.013

Espinet, J. M., Saez, M., Coenders, G., & Fluvià, M. (2003). Effect on prices of the attributes of holiday hotels: a hedonic prices approach. *Tourism Economics*, *9*(2), 165–177. http://doi.org/10.5367/000000003101298330

Estárico, E. H., Medina, L. F., & Marrero, S. M. (2012). Una aproximación a la reputación en línea de los establecimientos hoteleros españoles. *Papers de Turisme*, (52), 63–88.

Fang, B., Ye, Q., Kucukusta, D., & Law, R. (2016). Analysis of the perceived value of online tourism reviews: Influence of readability and reviewer characteristics. *Tourism Management*, *52*, 498–506. https://doi.org/10.1016/j.tourman.2015.07.018

Faraway, J. J. (2014). *Linear models with R*. BOOK, CRC Press.

Fernández-Barcala, M., González-Díaz, M., & Prieto-Rodríguez, J. (2010). Hotel quality appraisal on the Internet: a market for lemons? *Tourism Economics*, *16*(2), 345–360. http://doi.org/10.5367/000000010791305635

Filieri, R., & McLeay, F. (2013). E-WOM and Accommodation: An Analysis of the Factors That Influence Travelers' Adoption of Information from Online Reviews. *Journal of Travel Research*, *53*(1), 44–57. http://doi.org/10.1177/0047287513481274

Filieri, R., Alguezaui, S. & McLeay, F. (2015). Why do travelers trust TripAdvisor? Antecedents of trust towards consumer-generated media and its influence on recommendation adoption and word of mouth. *Tourism Management*, 51,174–185. https://doi.org/10.1016/j.tourman.2015.05.007

Fuchs, M., & Zanker, M. (2012). Multi-criteria Ratings for Recommender Systems: An Empirical Analysis in the Tourism Domain (pp. 100–111). http://doi.org/10.1007/978-3-642-32273-0_9

Geerts, W. (2016). *Top 100 City Destinations Ranking*. Retrieved from http://blog.euromonitor.com/2016/01/top-100-city-destinations-ranking-2016.html

Gerrard, N. (2012). Battle with TripAdvisor won but the war goes on. *Caterer & Hotelkeeper*, *202*, 5. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=hjh&AN=72953162&lang=es&site=ehost-live&scope=site

Ghose, A., Ipeirotis, P. G., & Li, B. (2012). Designing ranking systems for hotels on travel search engines by mining user-generated and crowdsourced content. *Marketing Science*, *31*(3), 493–520. https://doi.org/10.1287/mksc.1110.0700

Gligorijevic, B. (2016). Review platforms in destinations and hospitality. In *Open Tourism*, (pp. 215–228). Springer.

Godes, D., & Mayzlin, D. (2004). Using Online Conversations to Study Word-of-Mouth Communication. *Marketing Science*, *23*(4), 545–560. http://doi.org/10.1287/mksc.1040.0071

Gretzel, U., & Yoo, K. H. (2008). Use and Impact of Online Travel Reviews. In P. O'Connor, W. Höpken, & U. Gretzel (Eds.), *Information and Communication Technologies in Tourism* (pp. 35–46). Vienna: Springer Vienna. http://doi.org/10.1007/978-3-211-77280-5_4

Grindlinger, G. S. (2012). Federal court dismisses defamation claims against TripAdvisor. *Hospitality Law*, *27*, 1–4. Retrieved from http://search.ebscohost.com/login.aspx?direct=true&db=hjh&AN=83716061&lang=es&site=ehost-live&scope=site

Gutiérrez Taño, D., Parra López, E., & González Wetherill, Y. C. (2014). La influencia de la autentificación de identidad en las valoraciones online de los hoteles. In *XVIII Congreso Nacional Asociación Española de Experto Cientificos en Turismo*. Benidorm.

Guttentag, D. (2015). Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector. *Current Issues in Tourism*, *18*(12), 1192–1217.

http://doi.org/10.1080/13683500.2013.827159
Guttentag, D. A., & Smith, S. L. J. (2017). Assessing Airbnb as a disruptive innovation relative to hotels: Substitution and comparative performance expectations. *International Journal of Hospitality Management*, *64*, 1–10. http://doi.org/10.1016/j.ijhm.2017.02.003

Hamilton, J. M. (2007). Coastal landscape and the hedonic price of accommodation. *Ecological Economics*, *62*(3), 594–602. https://doi.org/10.1016/j.ecolecon.2006.08.001

Harford, T. (2010). *The undercover economist*, Hachette UK.

Harrington, R. (2015). Vacation rentals: Commercial activity butting heads with CC&Rs. *California Western Law Review*, *51*(2), 187–224.

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? *Journal of Interactive Marketing*, *18*(1), 38–52. http://doi.org/10.1002/dir.10073

Hensel, K., & Deis, M. H. (2010). Using social media to increase advertising and improve marketing. *Entrepreneurial Executive*, *15*, 87–98.

Hong, T. (2006). The influence of structural and message features on Web site credibility. *Journal of the American Society for Information Science and Technology*, *57*(1), 114–127. http://doi.org/10.1002/asi.20258

Hotrec. (2015). Hotrec. Retrieved from http://www.hotrec.eu/newsroom/press-releases-1714/hotelstars-union-polished-the-criteria-for-its-hotelstars-categories.aspx

Hsu, C.-W., & Lin, C.-J. (2002). A comparison of methods for multiclass support vector machines. *IEEE Transactions on Neural Networks*, *13*(2), 415–425.

Hsu, C.-W., Chang, C.-C., & Lin, C.-J. (2003). A practical guide to support vector classification.

Hu, N., Bose, I., Gao, Y., & Liu, L. (2011). Manipulation in digital word-of-mouth: A reality check for book reviews. *Decision Support Systems*, *50*(3), 627–635. doi:10.1016/j.dss.2010.08.013

Hu, N., Pavlou, P. A., & Zhang, J. (2006). Can online reviews reveal a product's true quality?: empirical findings and analytical modeling of Online word-of-mouth communication. In *Proceedings of the 7th ACM conference on Electronic commerce*. 324–330. ACM.

Hvass, K. A., & Munar, A. M. (2012). The takeoff of social media in tourism. *Journal of Vacation Marketing*, *18*(2), 93–103. http://doi.org/10.1177/1356766711435978

Ince, D. C., Hatton, L., & Graham-Cumming, J. (2012). The case for open computer programs. Nature, 482(7386), 485-488. https://doi.org/10.1038/nature10836

Ingram, P. (1996). Organizational form as a solution to the problem of credible commitment: The evolution of naming strategies among US hotel chains, 1896–1980. *Strategic Management Journal*, *17*(S1), 85–98. https://doi.org/10.1002/smj.4250171007

Israeli, A. A. (2002). Star rating and corporate affiliation: their influence on room price and performance of hotels in Israel. *International Journal of Hospitality Management*, *21*(4), 405–424. http://doi.org/10.1016/S0278-4319(02)00037-3

Jeacle, I., & Carter, C. (2011). In TripAdvisor we trust: Rankings, calculative regimes and abstract systems. *Accounting, Organizations and Society*, *36*(4–5), 293–309. http://doi.org/10.1016/j.aos.2011.04.002

Jin, G. Z., & Whalley, A. (2007). The Power of Information: How Do US News Rankings Affect the Financial Resources of Public Colleges? JOUR.

Karakaya, F., & Barnes, N. G. (2010). Impact of online reviews of customer care experience on brand or company selection. *Journal of Consumer Marketing*, *27*(5), 447–457. http://doi.org/10.1108/07363761011063349

Kim, M.-J., Chung, N., & Lee, C.-K. (2011). The effect of perceived trust on electronic commerce: Shopping online for tourism products and services in South Korea. *Tourism Management*, *32*, 256–265. http://doi.org/10.1016/j.tourman.2010.01.011

Kwok, L., Xie, K. L., & Richards, T. (2017). Thematic framework of online review research: A systematic analysis of contemporary literature on seven major hospitality and tourism journals. *International Journal of Contemporary Hospitality Management*, *29*(1), 307–354. https://doi.org/10.1108/IJCHM-11-2015-0664

Lant, T. K., & Baum, J. A. C. (1995). Cognitive sources of socially constructed competitive groups: Examples from the Manhattan hotel industry. *The Institutional Construction of Organizations*, *15*, 38.

Law, R. (2006). Internet and Tourism—Part XXI: TripAdvisor. *Journal of Travel Tourism Marketing*, *20*, 75–77. http://doi.org/10.1300/J073v20n01-06

Lee, J., Park, D.-H., & Han, I. (2008). The effect of negative online consumer reviews on product attitude: An information processing view. *Electronic Commerce Research and Applications*, *7*(3), 341–352. http://doi.org/10.1016/j.elerap.2007.05.004

Leung, D., Law, R., van Hoof, H., & Buhalis, D. (2013). Social Media in Tourism and Hospitality: A Literature Review. *Journal of Travel and Tourism Marketing*, *30*(1-2), 3–22. http://doi.org/10.1080/10548408.2013.750919

Leung, D., Lee, H. A., & Law, R. (2011). The Impact of Culture on Hotel Ratings: Analysis of Star-Rated Hotels in China. *Journal of China Tourism Research*, *7*(3), 243–262. http://doi.org/10.1080/19388160.2011.599239

Leung, X. Y., Bai, B., & Erdem, M. (2017). Hotel social media marketing: a study on message strategy and its effectiveness. *Journal of Hospitality and Tourism Technology*, *8*(2), 239–255. http://doi.org/10.1108/JHTT-02-2017-0012

Liang, S., Schuckert, M., Law, R., & Chen, C.-C. (2017). Be a “Superhost”: The importance of badge systems for peer-to-peer rental accommodations. *Tourism Management*, *60*, 454–465. https://doi.org/10.1016/j.tourman.2017.01.007

Litvin, S. W., Goldsmith, R. E., & Pan, B. (2008). Electronic word-of-mouth in hospitality and tourism management. *Tourism Management*, *29*(3), 458–468. http://doi.org/10.1016/j.tourman.2007.05.011

Liu, B., Pennington-Gray, L., Donohoe, H., & Omodior, O. (2015). New York City Bed Bug Crisis as Framed by Tourists on Tripadvisor. *Tourism Analysis*, *20*(2), 243–250. http://doi.org/10.3727/108354215X14265319207597

Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing*, *70*(3), 74–89. JOUR.

López Fernández, M. C., & Serrano Bedia, A. M. (2004a). Is the hotel classification system a good indicator of hotel quality? *Tourism Management*, *25*(6), 771–775. http://doi.org/10.1016/j.tourman.2004.06.007

Manes, E., & Tchetchik, A. (2018). The role of electronic word of mouth in reducing information asymmetry: An empirical investigation of online hotel booking. *Journal of Business Research*, *85*, 185–196. http://doi.org/https://doi.org/10.1016/j.jbusres.2017.12.019

Marine-Roig, E. (2017). Online travel reviews: A massive paratextual analysis. In Z. Xiang & D. R. Fesenmaier (Eds.), *Analytics in Smart Tourism design: Concepts and methods* (pp. 179–202). Heidelberg, Germany: Springer. http://doi.org/10.1007/978-3-319-44263-1_11

Marine-Roig, E., Martin-Fuentes, E., & Daries-Ramon, N. (2017). User-Generated Social Media Events in Tourism. *Sustainability, 9*(12), 22–50. http://doi.org/10.3390/su9122250

Martin-Fuentes, E., Daries-Ramon, N & Marine-Roig, E., (2015). Satisfacción y fuentes de información de los estudiantes de movilidad universitarios. *Opción*, *31*(Especial 2), 712–729.

Martin-Fuentes, E., Fernandez, C., & Mateu, C. (2016). Las estrellas muestran el camino: coincidencia entre satisfacción y categoría hotelera. In Universidad de Malaga (Ed.), *ICT & Tourism International Conference TURITEC*. Málaga (Spain).

Masiero, L., Nicolau, J. L., & Law, R. (2015). A demand-driven analysis of tourist accommodation price: A quantile regression of room bookings. *International Journal of Hospitality Management*, *50*, 1–8. https://doi.org/10.1016/j.ijhm.2015.06.009

Mayzlin, D., Dover, Y., & Chevalier, J. A. (2012). Promotional reviews: An empirical investigation of online review manipulation. *American Economic Review*, *104*(8), 2421–55. https://doi.org/10.1257/aer.104.8.2421

González, S. M., Gidumal, J. B., & López-Valcárcel, B. G. (2010). La participación de los clientes en sitios web de valoración de servicios turísticos. El caso de TripAdvisor. *Análisis Turístico*, *10*, 17–22. https://doi.org/10.1234/RAT2011n11

Melian-Gonzalez, S., Bulchand-Gidumal, J., & Gonzalez Lopez-Valcarcel, B. (2013). Online Customer Reviews of Hotels: As Participation Increases, Better Evaluation Is Obtained. *Cornell Hospitality Quarterly*, *54*(3), 274–283. http://doi.org/10.1177/1938965513481498

Mellinas Cánovas, J. P. (2015). *Análisis y aplicaciones de los sistemas de medición de la reputación online de los hoteles*. Universidad Politécnica de Cartagena.

Mellinas, J. P., Martínez María-Dolores, S.-M., & Bernal García, J. J. (2015). Booking.com: The unexpected scoring system. *Tourism Management*, *49*, 72–74. http://doi.org/10.1016/j.tourman.2014.08.019

Mellinas, J. P., Martínez María-Dolores, S.-M., & Bernal García, J. J. (2016). *Effects of the Booking.com scoring system*. *Tourism Management, 57,* 80–83. https://doi.org/10.1016/j.tourman.2016.05.015

Memarzadeh, F., Blum, S. C., & Adams, C. (2015). The impact of positive and negative e-comments on business travelers' intention to purchase a hotel room. *Journal of Hospitality and Tourism Technology*, *6*(3), 258–270. http://doi.org/10.1108/JHTT-09-2014-0049

Miah, S. J., Vu, H. Q., Gammack, J., & McGrath, M. (2017). A big data analytics method for tourist behaviour analysis. *Information & Management, 54*(6), 771–785. https://doi.org/10.1016/j.im.2016.11.011

Minazzi, R. (2010). Hotel classification systems: a comparison of international case studies. *Acta Universitatis Danubius. Œconomica*, *6*(4), 64–86.

Mkono, M. (2015). "Troll alert!": Provocation and harassment in tourism and hospitality social media. *Current Issues in Tourism*, 1–14. http://doi.org/10.1080/13683500.2015.1106447

Möhlmann, M. (2015). Collaborative consumption: determinants of satisfaction and the likelihood of using a sharing economy option again. *Journal of Consumer Behaviour*, *14*(3), 193–207. http://doi.org/10.1002/cb.1512

Monty, B., & Skidmore, M. (2003). Hedonic Pricing and Willingness to Pay for Bed and Breakfast Amenities in Southeast Wisconsin. *Journal of Travel Research*, *42*(2), 195–199. http://doi.org/10.1177/0047287503257500

Morgan, N. J., Pritchard, A., & Piggott, R. (2003). Destination branding and the role of the stakeholders: The case of New Zealand. *Journal of Vacation Marketing*, *9*, 285–299. https://doi.org/10.1177/135676670300900307

Morosan, C. (2013). The Impact of the Destination's Online Initiatives on Word of Mouth. *Tourism Analysis*, *18*(4), 415–428. http://doi.org/10.3727/108354213X13736372325993

Morrison, S. (2012). TripAdvisor Under Fire for "Real Traveller" Contribution Claim. Retrieved December 10, 2015, from http://www.guardian.co.uk/media/2012/feb/01/tripadvisor-criticise-honest-contribution-claim

Munar, A. M. (2011). Tourist-created content: rethinking destination branding. *International Journal of Culture, Tourism and Hospitality Research*, *5*(3), 291–305. http://doi.org/10.1108/17506181111156989

Narangajavana, Y., & Hu, B. (2008). The Relationship Between the Hotel Rating System, Service Quality Improvement, and Hotel Performance Changes: A Canonical Analysis of Hotels in Thailand. *Journal of Quality Assurance in Hospitality & Tourism*, *9*(1), 34–56. http://doi.org/10.1080/15280080802108259

Neirotti, P., Raguseo, E., & Paolucci, E. (2016). Are customers' reviews creating value in the hospitality industry? Exploring the moderating effects of market positioning. *International Journal of Information Management*, *36*(6), 1133–1143. http://doi.org/10.1016/j.ijinfomgt.2016.02.010

Nicolau, J. L., & Sellers, R. (2010). The quality of quality awards: Diminishing information asymmetries in a hotel chain. *Journal of Business Research*, *63*(8), 832–839. doi:10.1016/j.jbusres.2009.06.009

Núñez-Serrano, J. A., Turrión, J., & Velázquez, F. J. (2014). Are stars a good indicator of hotel quality? Assymetric information and regulatory heterogeneity in Spain. *Tourism Management*, *42*, 77–87. http://doi.org/10.1016/j.tourman.2013.10.004

O'Connor, P. (2008). User-Generated Content and Travel : A Case Study on Tripadvisor.Com. *Business*, *21*, 47–58. http://doi.org/10.1007/978-3-211-77280-5_5

O'Connor, P. (2010). Managing a Hotel's Image on TripAdvisor. *Journal of Hospitality Marketing & Management*. doi:10.1080/19368623.2010.508007

Öğüt, H., & Onur Taş, B. K. (2012). The influence of internet customer reviews on the online sales and prices in hotel industry. *The Service Industries Journal*, *32*(2), 197–214. http://doi.org/10.1080/02642069.2010.529436

Palmer, M. (2013). It's the hotel review website that millions use to help choose their holiday. But… Can you trust a single word on TripAdvisor? Retrieved September 11, 2014, from http://www.dailymail.co.uk/news/article-2384519/Its-hotel-review-website-millions-use-help-choose-holiday-But--Can-trust-single-word-Trip-Advisor.html

Pan, B., MacLaurin, T., & Crotts, J. C. (2007). Travel blogs and the implications for destination marketing. *Journal of Travel Research*, *46*(1), 35–45. https://doi.org/10.1177/0047287507302378

Pantelidis, I. S. (2010). Electronic Meal Experience: A Content Analysis of Online Restaurant Comments. *Cornell Hospitality Quarterly*, *51*(4), 483–491. http://doi.org/10.1177/1938965510378574

Park, D.-H., Lee, J., & Han, I. (2007). The Effect of On-Line Consumer Reviews on Consumer Purchasing Intention: The Moderating Role of Involvement. *International Journal of Electronic Commerce*, *11*(4), 125–148. http://doi.org/10.2753/JEC1086-4415110405

Park, S., & Nicolau, J. L. (2015). Asymmetric effects of online consumer reviews. *Annals of Tourism Research*, *50*, 67–83. http://doi.org/10.1016/j.annals.2014.10.007

Pavlou, P. A., & Dimoka, A. (2006). The nature and role of feedback text comments in online marketplaces: Implications for trust building, price premiums, and seller differentiation. *Information Systems Research*, *17*(4), 392–414.

Petz, G., & Greiner, A. (2014). First in Search–How to Optimize Search Results in E-Commerce Web Shops. In *HCI in Business* (pp. 566–574). Springer.

Pirolli, B. (2016). Travel information online: navigating correspondents, consensus, and conversation. *Current Issues in Tourism*, (in press), 1–7. http://doi.org/10.1080/13683500.2016.1273883

Plé, L., & Chumpitaz Cáceres, R. (2010). Not always co-creation: introducing interactional co-destruction of value in service-dominant logic. *Journal of Services Marketing, 24*(6), 430-437. https://doi.org/10.1108/08876041011072546

Pope, D. G. (2009). Reacting to rankings: evidence from "America's Best Hospitals". *Journal of Health Economics*, *28*(6), 1154–65. http://doi.org/10.1016/j.jhealeco.2009.08.006

Racherla, P., Connolly, D. J., & Christodoulidou, N. (2013). What Determines Consumers' Ratings of Service Providers? An Exploratory Study of Online Traveler Reviews. *Journal of Hospitality Marketing & Management*, 22(2), 135–161. http://doi.org/10.1080/19368623.2011.645187

Ratcliff, J. W., & Metzener, D. E. (1988). Pattern-matching-the gestalt approach. *Dr Dobbs Journal*, *13*(7), 46.

Rawlinson, K. (2011). Hotelier's business collapses after "good" reviews on website. Retrieved from http://www.independent.co.uk/travel/news-and-advice/hoteliers-business-collapses-after-good-reviews-on-website-2363191.html

Rifkin, J. (2000). The age of access: The new culture of cypercapitalism. Where All of Life Is a Paid-For Experience. *Tarcher-Putman Books, New York*, 228.

Saló, A., Garriga, A., Rigall-I-Torrent, R., Vila, M., & Fluvià, M. (2014). Do implicit prices for hotels and second homes show differences in tourists' valuation for public attributes for each type of accommodation facility? *International Journal of Hospitality Management*, *36*, 120–129. doi:10.1016/j.ijhm.2013.08.011

Schuckert, M., Liu, X., & Law, R. (2015). Hospitality and Tourism Online Reviews: Recent Trends and Future Directions. *Journal of Travel & Tourism Marketing*, *32*(5), 608–621. http://doi.org/10.1080/10548408.2014.933154

Sigala, M. (2008). Web 2.0, social marketing strategies and distribution channels for city destinations. In G.-H. & Torres-Coronas (Ed.), *Information Communication Technologies and City Marketing* (pp. 220–244). Hershey, New York, USA: Information Science Reference.

Sigala, M. (2015). Collaborative commerce in tourism: implications for research and industry. *Current Issues in Tourism*, 1–10.

http://doi.org/10.1080/13683500.2014.982522

Sigala, M., Christou, E., & Gretzel, U. (2012). *Social media in travel, tourism and hospitality: Theory, practice and cases*. (M. Sigala, E. Christou, & U. Gretzel, Eds.). Surrey, England: Ashgate Publishing.

Smith, O. (2012). TripAdvisor under fire over fraud detection. Retrieved September 3, 2014, from http://www.telegraph.co.uk/travel/travelnews/9160472/TripAdvisor-under-fire-over-fraud-detection.html

Solomon, M., Russell-Bennett, R., & Previte, J. (2012). *Consumer behaviour*. BOOK, Pearson Higher Education AU.

Sorensen, A. T. (2007). Bestseller lists and product variety. *The Journal of Industrial Economics*, *55*(4), 715–738. https://doi.org/10.1111/j.1467-6451.2007.00327.x

Sparks, B. A., & Browning, V. (2011). The impact of online reviews on hotel booking intentions and perception of trust. *Tourism Management*, *32*(6), 1310–1323. https://doi.org/10.1016/j.tourman.2010.12.011

Spink, A., & Jansen, B. J. (2006). *Web search: Public searching of the Web* (Vol. 6). BOOK, Springer Science & Business Media.

Steffes, E. M., & Burgee, L. E. (2009). Social ties and online word of mouth. *Internet research*, *19*(1), 42-59. https://doi.org/10.1108/10662240910927812

Stiglitz, J. E. (2002). Information and the Change in the Paradigm in Economics. *The American Economic Review*, *92*(3), 460–501. https://doi.org/10.1257/00028280260136363

Striphas, T. (2015). Algorithmic culture. *European Journal of Cultural Studies*, *18*(4–5), 395–412. http://doi.org/10.1177/1367549415577392

Sun, S., Fong, L. H. N., Law, R., & Luk, C. (2015). An Investigation of Gen-Y's Online Hotel Information Search: The Case of Hong Kong. *Asia Pacific Journal of Tourism Research*, 1–14. http://doi.org/10.1080/10941665.2015.1062405

Susskind, A. (2002). I told you so! Restaurant customers' word-of-mouth communication patterns. *The Cornell Hotel and Restaurant Administration Quarterly*, *43*(2), 75–85. http://doi.org/10.1016/S0010-8804(02)80034-9

Torres, E. N., Adler, H., & Behnke, C. (2014). Stars, diamonds, and other shiny things: The use of expert and consumer feedback in the hotel industry. *Journal of Hospitality and Tourism Management*, *21*, 34–43. http://doi.org/10.1016/j.jhtm.2014.04.001

TripAdvisor. (2013). The TripAdvisor Incentives Policy: Why Rewarding Traveller Reviews Is Against The Rules, retrieved January 10, 2018, from https://www.tripadvisor.com/TripAdvisorInsights/w591

TripAdvisor. (2014). TripAdvisor Help Center. Retrieved May 13, 2016, from https://www.tripadvisorsupport.com/hc/en-us/articles/200614057

TripAdvisor. (2016a). Retrieved August 5, 2016, from https://www.tripadvisor.com/PressCenter-c6-About_Us.html

TripAdvisor. (2016b). TripAdvisor. Retrieved November 8, 2016, from https://www.tripadvisorsupport.com/hc/en-us/articles/215955068

TripAdvisor. (2016c). Changes to the TripAdvisor Popularity Ranking Algorithm. Retrieved November 24, 2016, from https://www.tripadvisor.co.uk/TripAdvisorInsights/n2701/changes-tripadvisor-popularity-ranking-algorithm

TripAdvisor. (2018). About TripAdvisor. Retrieved January 10, 2018, from https://tripadvisor.mediaroom.com/us-about-us

Tussyadiah, I. P., & Pesonen, J. (2016). Drivers and barriers of peer-to-peer accommodation stay – an exploratory study with American and Finnish travellers. *Current Issues in Tourism*, 1–18. http://doi.org/10.1080/13683500.2016.1141180

Tussyadiah, I. P., & Pesonen, J. (2016). Impacts of Peer-to-Peer Accommodation Use on Travel Patterns. *Journal of Travel Research*, *55*(8), 1022–1040. https://doi.org/10.1177/0047287515608505

Tussyadiah, I. P., & Zach, F. (2017). Identifying salient attributes of peer-to-peer accommodation experience. *Journal of Travel & Tourism Marketing*, *34*(5), 636–652. http://doi.org/10.1080/10548408.2016.1209153

Vapnik, V. (1995). The nature of statistical learning theory. Springer Heidelberg.

Varma, A., Jukic, N., Pestek, A., Shultz, C. J., & Nestorov, S. (2016). Airbnb: Exciting innovation or passing fad? *Tourism Management Perspectives*, *20*, 228–237. http://doi.org/10.1016/j.tmp.2016.09.002

Vásquez, C. (2011). Complaints online: The case of TripAdvisor. *Journal of Pragmatics*, *43*(6), 1707–1717. http://doi.org/10.1016/j.pragma.2010.11.007

Vermeulen, I. E., & Seegers, D. (2009). Tried and tested: The impact of online hotel reviews on consumer consideration. *Tourism Management*, *30*(1), 123–127. doi:10.1016/j.tourman.2008.04.008

Viglia, G., Furlan, R., & Ladrón-de-Guevara, A. (2014). Please, talk about it! When hotel popularity boosts preferences. *International Journal of Hospitality Management*, *42*, 155–164. http://doi.org/10.1016/j.ijhm.2014.07.001

Viglia, G., Minazzi, R., & Buhalis, D. (2016). The influence of e-word-of-mouth on hotel occupancy rate. *International Journal of Contemporary Hospitality Management*, *28*(9), 2035–2051. http://dx.doi.org/10.1108/IJCHM-05-2015-0238

Wang, D., & Nicolau, J. L. (2017). Price determinants of sharing economy based accommodation rental: A study of listings from 33 cities on Airbnb.com. *International Journal of Hospitality Management*, *62*, 120–131. http://doi.org/10.1016/j.ijhm.2016.12.007

Wathieu, L., Brenner, L., Carmon, Z., Chattopadhyay, A., Wertenbroch, K., Drolet, A., Gourville, J., Muthukrishnan, A.V., Novemsky, N., Ratner, R. K., & Wu, G. (2002). Consumer control and empowerment: A primer. *Marketing Letters*, *13*(3), 297–305. https://doi.org/10.1023/A:1020311914022

Webb, S. (2014). "Give us free meals or I"ll put a bad review on TripAdvisor': Anger at blackmailers using online ratings website to extort free rooms and dinners from hotels and restaurants. Retrieved December 10, 2015, from http://www.dailymail.co.uk/news/article-2623290/Give-free-meals-Ill-bad-review-TripAdvisor-Anger-blackmailers-using-online-ratings-website-extort-free-rooms-dinners-hotels-restaurants.html

Wilson, T. (2012). Hotels as Ready-to-Hand Recreation: TripAdvisors Posting Potentiality-for-Being in Play. *Tourist Studies*, *12*(1), 70–86. http://doi.org/10.1177/1468797612444198

Xiang, Z., & Gretzel, U. (2010). Role of social media in online travel information search. *Tourism Management*, *31*(2), 179–188. http://doi.org/10.1016/j.tourman.2009.02.016

Xiang, Z., Du, Q., Ma, Y., & Fan, W. (2017). A comparative analysis of major online review platforms: Implications for social media analytics in hospitality and tourism. *Tourism Management*, *58*, 51–65. http://doi.org/10.1016/j.tourman.2016.10.001

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

Xie, K. L., Zhang, Z., & Zhang, Z. (2014). The business value of online consumer reviews and management response to hotel performance. *International Journal of Hospitality Management*, *43*, 1–12. http://doi.org/10.1016/j.ijhm.2014.07.007

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

Ye, Q., Law, R., Gu, B., & Chen, W. (2011). The influence of user-generated content on traveler behavior: An empirical investigation on the effects of e-word-of-mouth to hotel online bookings. *Computers in Human Behavior*, *27*(2), 634–639. http://doi.org/10.1016/j.chb.2010.04.014

Yen, C.-L. (Alan), & Tang, C.-H. (Hugo). (2015). Hotel attribute performance, eWOM motivations, and media choice. *International Journal of Hospitality Management*, *46*, 79–88. http://doi.org/10.1016/j.ijhm.2015.01.003

Yoo, K. H., & Gretzel, U. (2010). Antecedents and impacts of trust in travel-related consumer-generated media. *Information Technology & Tourism*, *12*(2), 139–152. https://doi.org/10.3727/109830510X12887971002701

Yoo, K.-H., Sigala, M., & Gretzel, U. (2016). Exploring TripAdvisor. In R. Egger, I. Gula, & D. Walcher (Eds.), *Open Tourism: Open Innovation, Crowdsourcing and Co-Creation Challenging the Tourism Industry* (pp. 239–255). inbook, Berlin, Heidelberg: Springer Berlin Heidelberg. http://doi.org/10.1007/978-3-642-54089-9_17

Zeithaml, V. A., Berry, L. L., & Parasuraman, A. (1993). The nature and determinants of customer expectations of service. *Journal of the Academy of Marketing Science*, *21*(1), 1–12. https://doi.org/10.1177/0092070393211001

Zervas, G., Proserpio, D., & Byers, J. (2015). A First Look at Online Reputation on Airbnb, Where Every Stay is Above Average. *(January 28, 2015)*. Available at SSRN: https://ssrn.com/abstract=2554500

Zhan-Qing, L., & Liu, J. C. (1993). Assessment of the hotel rating system in China. *Tourism Management*, *14*(6), 440–452. https://doi.org/10.1016/0261-5177(93)90097-5

Zhang, Z., Ye, Q., & Law, R. (2011). Determinants of hotel room price. *International Journal of Contemporary Hospitality Management*, *23*(7), 972–981. doi:10.1108/09596111111167551

Zhang, Z., Zhang, Z., Wang, F., Law, R., & Li, D. (2013). Factors influencing the effectiveness of online group buying in the restaurant industry. International Journal of Hospitality Management, 35, 237–245. http://doi.org/10.1016/j.ijhm.2013.06.012

Zheng, W. & Ye, Q. (2009). Sentiment classification of Chinese traveler reviews by support vector machine algorithm. In Intelligent Information Technology Application, 2009. IITA 2009. Third International Symposium on. IEEE, pp. 335–338. http://doi.org/10.1109/IITA.2009.457

Zhou, X., Xu, Y., Li, Y., Josang, A., & Cox, C. (2012). The state-of-the-art in personalized recommender systems for social networking. Artificial Intelligence Review, 37(2), 119-132. https://doi.org/10.1007/s10462-011-9222-1

Zhu, F., & Zhang, X. (2010). Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of Marketing*, *74*(2), 133–148. https://doi.org/10.1509/jmkg.74.2.133

Zong, J., Tang, F., Huang, W., & Ma, J. (2010). Online Pricing Dispersion of Chinese Hotels. *Journal of China Tourism Research 4*(3-4), 248-260. http://doi.org/10.1080/19388160080250244