Branding luxury hotels: Evidence from the analysis of consumers' "big" visual data on TripAdvisor

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ABSTRACT

The aim of this paper is to understand consumers' perception of luxury hotel brands. To this end, the research evaluates consumers' "big" visual data on TripAdvisor through a machine learning approach. Results shed light on the significant part of non-textual elements of the hotel experience such as pictures, which cannot be explored through traditional methods as content analysis. In particular, the analysis of 7,395 consumers' pictures leads to the identification of the attributes that had the higher impact on their experience. These attributes emerged as specific features of interior elements of the hotels (rooms and restaurant).

Finally, the study shows how big data analytics and machine learning algorithms can (i) help monitoring social media and understand consumers perception of luxury hotels through the new analysis of visual data, and (ii) turn into better brand management strategies for luxury hotel managers.

1. Introduction

The increasing demand of luxury brands is adding complexity to the luxury marketplace, by positing new challenges for brand managers (Hennigs, Wiedmann, Behrens, & Klarmann, 2013). Success in brand management results from the right understanding of consumers' expectations and the ability of managers to reply accordingly to generate profitability (Atwal & Williams, 2009; Kim & Kim, 2005). Specifically, luxury hotel management is acquiring the interest of scholars and practitioners in both brand management and tourism management literature. Indeed, past studies made some attempts to understand the source of consumers' satisfaction with hotel brands through questionnaires (Chan & Guillet, 2011; Minazzi & Lagrosen, 2013; Lai & Hitchcock, 2017), online rating and sentiment analysis (Boo & Busser, 2018; Geetha, Singha, & Sinha, 2017; Pantano, Priporas, & Stylos, 2017), and social media interactions (Kim & Lee, 2019). Especially systematic social media monitor would allow understanding consumers' behavior and engagement with the brand (Liu, Shin, & Burns, in press; Swani, Milne, & Miller, in press). In this vein, big data analytics and machine learning techniques would support to gather online insights on consumers, with emphasis on social media sources. However, big data analytical tools are still scarcely explored in branding and luxury branding studies (Liu et al., in press; Pantano, Giglio, & Dennis, 2019).

Therefore, finding new approaches to monitor social media would help in understanding the unique characteristics of luxury brands shared through social media (Liu et al., in press), while machine learning algorithms would make this monitor happen.

Hence, two questions arise in this new competitive scenario:

RQ1: How can big data analytics and machine learning algorithms help monitoring social media and understand consumers' perception of luxury hotels?

RQ2: How can big data analytics turn into better brand management strategies for luxury hotel managers?

The aim of this paper is to understand consumers' perception of luxury hotel brands through systematically monitoring social media, resulting in better brand management strategies. To this end, the present study explored visual data emerged from 7,395 pictures posted in January 2018 by unique users, related to six different luxury hotels in central London (UK), which have been analyzed through *Wolfram Mathematica* software. Results allow understanding the different hotel attributes, with implications for scholars in tourism and brand management, and practitioners in hotel management. First, results highlight the extent to which big data analytics and machine learning algorithms support luxury hotel managers to more carefully and systematically monitor social media, with emphasis on visual data. Secondly, they allow understanding the different hotel attributes influencing

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consumers' evaluation of a certain luxury hotel through the analysis of consumer-generated pictures. Finally, the adopted methodology might be considered as a technique for a "dimensionality-reduction" of the volume of "big" visual data, while opening up the potential for new research methods in consumer behavior as never exploited before.

The paper is organized as it follows: the next section will review the current literature on brand management with emphasis on luxury brands and luxury hotel brands; the subsequent one synthetizes machine learning approaches to gather consumers' insights; the section on the research methodology and key findings will follow; finally, the paper concludes with a discussion of key results and implications for scholars and practitioners.

2. Theoretical background

Recent studies demonstrated the extent to which the image of a certain destination influences tourists' behavior prior to, during, and after visiting a certain place (Tasci, 2018). Indeed, pictures are among the preferred contents included in online posts, able to enhance the attractiveness, by providing a virtual access to the hotel features (Chan & Guillet, 2011; Minazzi & Lagrosen, 2013). To this end, social media like Instagram and Facebook are also used for branding places. This usage does not imply the generation of new images, but the set of a certain choreography according to the functionalities of the medium (i.e., the choice of particular filters to improve the quality of the image or to add appealing digital effects) (Thelander & Cassinger, 2017). Thus, the presence on social media as part of marketing campaign has become a consolidated practice for brand managers (Hsu, Wang, Chih, & Lin, 2015; Pantano & Di Pietro, 2013). For instance, this presence allows firm to both find new customers (also exploiting the electronic word of mouth communication- eWOM), and to maintain and retain the existing ones, who can consider this digital tool as a direct channel to interact with the brand (Lim, Hwang, Kim, & Biocca, 2015; Luo, Zhang, & Liu, 2015). From a brand management perspective, the exploitation of fan pages on social media like Facebook further allows brand to increase reputation (Lee, Kim, & Kim, 2012) and awareness (Chen, Lu, Wang, Zhao, & Li, 2013), as well as to develop and disseminate corporate identity (Devereux, Melewar, & Foroudi, 2017).

More specifically, specialized tourism platforms like TripAdvisor or Booking provide travelers with the access to a massive amount of online reviews to support their choice when planning holidays. Indeed, TripAdvisor is considered the largest travel platform with more than 455 million average monthly unique visitors and over 630 million reviews of hotels, restaurants, and attractions related businesses (TripAdvisor, 2018). In particular, the platform collects consumers' rating, ranking, and pictures that are freely accessible without registration or login. Since taking pictures allows tourists to share with other the meaningful tourism experience lived in a certain place, sharing pictures online allows tourists to get the appreciation of others including strangers, by improving the experience in a sort of "hermeneutic circle" (Balomenou & Garrod, 2019; Garrod, 2008; Lo & McKercher, 2015; Mang, Piper, & Brown, 2016; Nikjoo & Bakhshi, 2019). For this reason, an increasing number of studies in tourism considers pictures taken by tourists as rich data sources for tourism research (Balomenou & Garrod, 2019; Balomenou, Garrod, & Gerogiadou, 2017; Donaire, Camprubi, & Gali, 2014; Konijin, Sluimer, & Miras, 2016; Kim & Stepchenkova, 2015; Nikjoo & Bakhshi, 2019; Pearce & Wang, 2019), able to support the deeper understanding of consumers' perception of hotel brand image (O'Connor, 2010), destination attractiveness (Jung, Tom Dieck, & Chung, 2018; Perez-Vega, Taheri, Farrington, & O'Gorman, 2018), and quality of tourism experience (Banerjee & Chua, 2016; Pantano et al., 2017). To this end, images based on their manifest content can be directly observed and quantitatively summarized with acceptable reliability (e.g. of co-occurrences and clustering) (Kim & Stepchenkova, 2015).

Due to the continuous growing in the tourist accommodation sector

(Eurostat, 2017) in line with the growth of luxury experiences in general (Boston Consultant Group (2015) (2015), 2015), the investigation of luxury hotel brands is emerging as a hot topic for current research in the both tourism (Chen & Peng, 2014; Díaz & Koutra, 2013; Liu, Wong, Tseng, Chang, & Phau, 2017; Yang, Zhang, & Mattila, 2016) and brand management literature (Kim & Kim, 2005; Lo, Im, Chen, & Qu, 2017; Xie, Li, Chen, & Huan, 2016). Differently to the other luxury sectors, the hotel industry is based on selling experiences rather than selling tangible goods, thus it aims at providing the superior service to meet customers' needs (Liang, 2008). Guests have turned into consumers when becoming more aware of the quality and value of services being provided by luxury hotels (Ariffin & Maghzi, 2012). Luxury hotel further shows characteristics of prestige, premium price, and intimate knowledge of guests (Sherman, 2005), and can be chosen by tourists for amenities such as room service, insured reservations, free parking, staff performance, and so on (Ariffin, Maghzi, Soon, & Alam, 2018; Zhang, Ye, & Law, 2011).

To date, studies on luxury hotel brand management mainly focus on the evaluation of the hotel brand experience and perceived service quality (Chen & Peng, 2014; Khan & Rahman, 2017; Lai & Hitchcock, 2017; Liu et al., 2017; Su & Reynolds, 2017; Wilkins, Merrilees, & Herington, 2007), price promotions (Yang et al., 2016), drivers of customer loyalty (Liang, 2008; Narteh, Agbemabiese, Kodua, & Braimah, 2013), and website performances (Diaz and Coutra) through traditional research methods such as interviews and surveys. However, how luxury hotel might benefit from the exploitation of social media and related analytics, with emphasis on big and visual data, to support brand management is still at an early stage (Rose & Willis, 2019). Accordingly, recent studies highlight the importance of digital and social media analytics to understand how exploiting social media presence to generate positive trust (Giglio, Bertacchini, Bilotta, & Pantano, 2019; Jung et al., 2018), and to investigate consumers' evaluations through online reviews analytics (Sun, Tong, & Law, 2015), suggesting for future research in this sense.

3. Machine learning approaches to gather consumers' insights from big data

The need to exploit big data to gain societal, economic value and to encourage the development of innovative products and services, and creating business value pushed researchers to develop more sophisticate tools of Artificial Intelligence roughly named "machine learning algorithms" (Alpaydin, 2014). Machine learning algorithms (MLs) is a field of theoretical investigation, mainly linked to Informatics and Artificial Intelligence, including a set of tools for classification and prediction exploiting structured and unstructured multimedia data (text, image, video and sound) in a variety of application domains. In particular, ML employs several methods and techniques such as object representation, model creation, optimization processes (Bayesian theorem) and neural networks.

These algorithms reduce the complexity of data, while searching for hidden pattern among huge quantity of clustered data. ML performs a basic cognitive function of the development of human cognition: learning through experience. Starting from the identification of a certain "law" on the scattered data, ML creates categories, similarly to childhood evolutionary processes for the development of conceptual categories holding during childhood. This process allows the learning system to recognize any input data that belongs to a specific category, even if data might vary slightly from the considered model, and takes place through (i) *representation*, a set of models that the learning algorithm can learn (the learning algorithm creates a model, the function that produces a given result for specific input), in other words the system creates a template that produces the desired results from the input data; (ii) *assessment*, the apprenticeship algorithm can create more than one model, a further evaluation function determines which of the models works better to deliver the desired result from specific

input sets (the evaluation function has the task of evaluating the created templates, since more than one model could provide useful results to solve a specific problem); and (iii) *optimization*, since the learning process produces a set of templates, which can usually generate the right result for a given set of inputs, through these models the learning process seeks to determine which one works better; finally the best model is selected due to the learning process.

Machine learning is generally based on supervised (supervised machine) or unsupervised algorithms (unsupervised machine). The supervised machines need a training set to train the system, assigning each object a reference category. These systems are called classifiers (the greater the complexity of the objects to be categorized and the number of categories, the larger the training set). For supervised classification systems, the most commonly used algorithms are Logistic Regression, Markovian models, Naive Bayes, Nearest Neighbor, Random Forest and Support Vector Machine or SVM algorithms. Unsupervised ML algorithms tend to cluster the objects that they consider into clusters, learning from data without a reference model. The number of clusters can be detected directly from the system or can be supplementary allocated. Specifically, during the unsupervised machine process, the model aims to find a structure in the inputs provided, without the input being labelled in any way (Love, 2002). The unsupervised classification systems relate to the discovery of patterns, and are largely used for predictions.

4. Methodology of research

Tourists' photographs posted online have been largely considered a rich data sets to support the deep understanding of behaviors and preferences (Balomenou & Garrod, 2019; Balomenou et al., 2017; MacKay & Couldwell, 2004; Pantano et al., 2017). Accordingly, ML algorithms can be successfully employed to mine information from unstructured data like images to explore lacks and assets of hotel services (Valdivia, Luzon, & Herrera, 2017). In the present study, the analysis consists of the identification of objects included in pictures posted online by consumers. To this goal, the research used ML algorithms, allowing to extract models and predictions on big data (Zhou, Pan, Wang, & Vasilakos, 2017). Specifically, the present work uses *Wolfram Mathematica* software that provides several pre-trained methods to manipulate and analyze a wide range of data in an easy and unified way (Zotos, 2007). Moreover, the software allows the direct collection of images from social media through its automated functions for classifying (supervised ML algorithms).

4.1. Data collection

We selected six luxury hotels in Central London (UK) and collected all the pictures posted by unique TripAdvisor users. In particular, the six hotels have the similar characteristics of (i) being in the same area, (ii) providing between 85 and 100 rooms (including suites) at comparable room rates (starting from 1,000 lb per night), facilities (i.e., swimming pool, Spa, airport transportation, etc.), and (iii) having more than 500 reviews on TripAdvisor. A total of 7,395 images were collected from consumers' reviews posted in January 2018 (Table 1).

Table 1
Number of photographs collected per each hotel in TripAdvisor.

Hotel	Consumers' photos on TripAdvisor
A	410
B	1,483
C	680
D	195
E	2,396
F	2,231

4.2. Procedure

The software already provides the function *ImageIdentify* (unsupervised machine learning algorithm), which allows recognising each object present in a certain picture, and assigns to each object the reference category, creating a classification. In this way, given the set of photos taken by tourists in the six hotels, the algorithm identifies the main object in each image returning the result into a specific category (Fig. 1). While manual categories have been developed to classify pictures on previous studies (Donaire et al., 2014), Wolfram Mathematica provides more than 10,000 categories to classify objects. The adopted algorithm is based on a particular kind of Artificial Intelligence named *deep learning*, aimed at simulating the human learning process in order to make the system able to self-improve as soon as new information are available (He, Zhang, Ren, & Sun, 2016; Najafabadi et al., 2015).

ImageIdentify provides a classification label, associating the recognition probability. The probability describes the identification degree of the object appearance using a value range from 0 to 1. To test the software and the probability of the right identification of the object, we provided to software some pictures taken by tourists in the luxury hotels suggesting a specific category ("bed" and "table"). The output shows the degree of accuracy with which the software achieves required goals. Fig. 2 shows the code adopted to test the performance and functioning of the algorithm. From a mathematical perspective, the software adopts the mathematical function with the highest probability of response on the dataset (Wolfram, 2016).

In the present study, the specific algorithm adopted a logistic regression as classifier machine. The logistic regression classifier models assign probabilities with logistic functions of linear combinations of features, including log-linear model, softmax regression, or maximum-entropy classifier (Hosmer, Lemeshow, & Sturdivant, 2013). Fig. 3 summarizes the classifier information about the selected method.

5. Findings

Each object included in a certain image per hotel has been classified in a specific category. Fig. 4 summarizes the results related to the ten most photographed objects per hotel, with the related number of pictures they appear.

Although consumers took different pictures in the hotels, giving attention to different objects, there are some recurrent elements in the pictures of the six hotels. Indeed, bedroom and dinner table are the most photographed ones, appearing as the first or the second element for each hotel. Subsequently, the top hotels attractions are the bathroom, double bed (appearing in five out of six hotel), and washbasin, living room, person and restaurant (appearing in four out of the six hotels related pictures) (Table 2).

Findings show that consumers are very attentive to the services quality of the private areas such as bedroom and bathroom, with emphasis in particular details such as the washbasin or the bed, this might imply a particular attention to both the cleanness and care of these elements. Taking pictures of these elements would also indicate attention to design and architecture, and comfort of the spaces where relaxing.

6. Discussion and conclusion

In the context of social media, consumers often tend to share their experience with a certain product/brand/company through unsolicited communication (user generated contents) that companies might monitor to get reliable insights (Liu et al., in press; Swani et al., in press). To date, research in branding mainly adopted traditional methodologies to collect data on consumers (i.e., interviews, surveys, questionnaires, etc.), and has rarely employed more than 1,000 individuals, while highlighting that there is a significant part of non-textual elements of the experience such as pictures that cannot be

```
aa = thumbnails = Table[Import[M1[[a]], "Image"],
   {a, Length[M1]}]
```



```
bb = ImageIdentify[aa]
```

{ reception desk , tiramisu , double bed , restaurant }

Fig. 1. Part of code and output for *ImageIdentify* function.

explored through traditional methods as content analysis. The present study was conducted with the aim of identifying the attributes of a luxury hotel that have the higher impact on consumers' evaluation of the hotel, with a new methodology capable to support the collection of "big" visual data. To this end, machine learning algorithms allow capturing, measuring, and analyzing luxury hotel's attributes as the main drivers of consumers' evaluation of the hotel experience through the collection and analysis of visual data from TripAdvisor. While past studies focus on *how* and *who* elements of photography (Lo & McKercher, 2015), the present study focuses on *what* to understand consumer behavior. In doing so, our results also suggest that research on the role of online images in shaping (luxury) hotel image needs to consider the progresses in machine learning algorithms. Accordingly,

Classifier information	
Method	Logistic regression
Number of classes	3
Number of features	1
Number of training examples	15
L1 regularization coefficient	0
L2 regularization coefficient	$1. \times 10^{-10}$

Fig. 3. Classifier information of Wolfram Mathematica specific algorithm.

```
bb = ImageIdentify[ [image] , "bed", 6, "Probability"]
```

⟨| double bed | → 0.596806, | trundle bed | → 0.39566, | single bed | → 0.0050244,
| hospital bed | → 0.0050244, | Murphy bed | → 0.0010193, | bed | → 1. |⟩

```
ImageIdentify[ [image] , "table", 6, "Probability"]
```

⟨| table | → 0.201171, | counter | → 0.195422, | work table | → 0.00387889,
| vanity | → 0.00116796, | bar | → 0.194936, | drafting table | → 0.00387889 |⟩
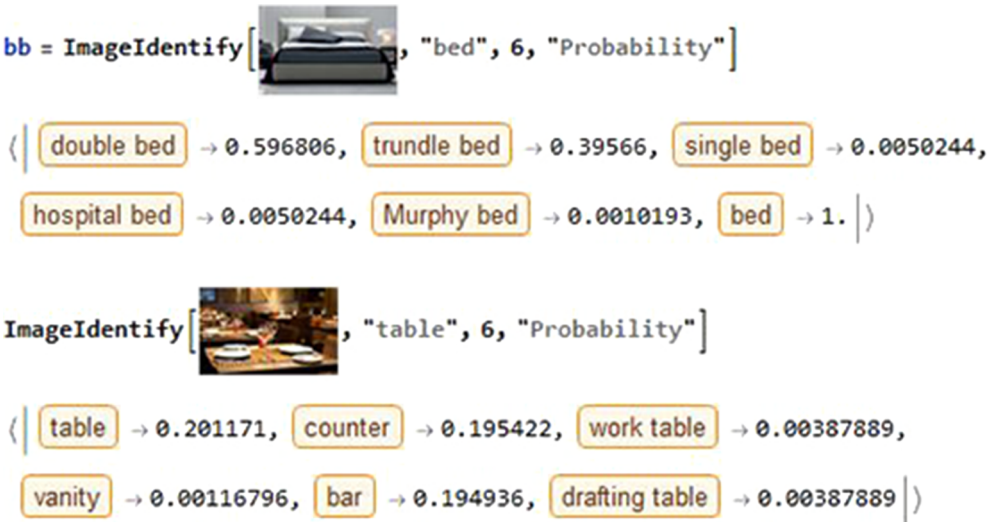
Fig. 2. Probability of right identification of the objects in pictures in *Wolfram Mathematica*.

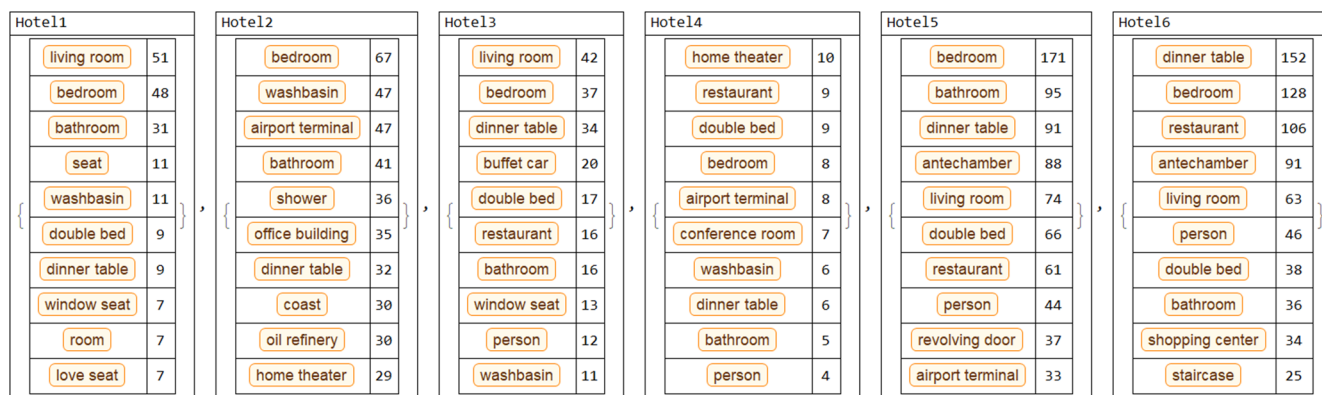| Hotel1		Hotel2		Hotel3		Hotel4		Hotel5		Hotel6	
living room	51	bedroom	67	living room	42	home theater	10	bedroom	171	dinner table	152
bedroom	48	washbasin	47	bedroom	37	restaurant	9	bathroom	95	bedroom	128
bathroom	31	airport terminal	47	dinner table	34	double bed	9	dinner table	91	restaurant	106
seat	11	bathroom	41	buffet car	20	bedroom	8	antechamber	88	antechamber	91
washbasin	11	shower	36	double bed	17	airport terminal	8	living room	74	living room	63
double bed	9	office building	35	restaurant	16	conference room	7	double bed	66	person	46
dinner table	9	dinner table	32	bathroom	16	washbasin	6	restaurant	61	double bed	38
window seat	7	coast	30	window seat	13	dinner table	6	person	44	bathroom	36
room	7	oil refinery	30	person	12	bathroom	5	revolving door	37	shopping center	34
love seat	7	home theater	29	washbasin	11	person	4	airport terminal	33	staircase	25

Fig. 4. The ten most photographed elements in luxury hotels.

our findings extend Kim and Stepchenkova (2015)'s work by providing a method to quantitatively summarize directly the manifest contents of visual images.

Since TripAdvisor further allows users to give an utility value to each review, the large presence of pictures of luxury hotels elements corroborate the previous studies on the sharing of online tourism pictures as a practice to get appreciation of others (Garrod, 2008; Balomenou & Garrod, 2019; Lo & McKercher, 2015; Mang et al., 2016; Nikjoo and Bakhshi, 2019). Similarly, our research evaluates pictures taken by tourists as a rich data source as per other tourism research (Balomenou & Garrod, 2019; Balomenou et al., 2017; Donaire et al., 2014; Konijin et al., 2016; Kim & Stepchenkova, 2015; Nikjoo and Bakhshi, 2019; Pearce & Wang, 2019). Therefore, we demonstrate that big data analytics and machine learning algorithms to evaluate consumers-generated photos enhance a more careful monitor of social media in the context of luxury hotel/brand management. In this vein, the study replies to the call for developing new analytics (with emphasis on social media analytics) to understand how exploiting social media presence for marketing and branding purposes (Jung et al., 2018; Sun et al., 2015). However, the identification of the right techniques would need specific analytical skills and software knowledge that might be not already available in hotel personnel.

Results also provide compelling evidence on the specific luxury hotel attributes able to influence consumers' perception at the most. As anticipated by MacKay and Couldwell (2004) in the context of generic tourists' pictures, keeping a visual inventory of the visitor's most attractive elements of a hotel can be capitalized by new marketing efforts. In this vein, Sun and colleagues (2017) initially proposed the main elements influencing the positive evaluation of hotel as rooms and facilities, the current study further categorized these elements into specific features as dinner table, bathroom, double bed, washbasin, living room, and restaurant. Also consumers evaluate more the overall quality of the room rather than the facilities and entertaining/leisure features (i.e., swimming pools) for the luxury ones. Although the employed ML algorithm is able to assign a label also to the exterior elements of the hotel (i.e., view/panorama, building, etc.), our findings suggest that tourists focused more on the interiors. Moreover, it seems that consumers tend to take a limited number of pictures (including selfies) in the luxury hotels. Nevertheless, the adopted methodology provides a more inclusive understanding of consumers' evaluation of the most important hotel attributes in the luxury domain, the importance of which is able to influence the hotel brand image generation.

Hotel and brand practitioners can benefit from new approaches like ours for monitoring social media, according to consumers' unsolicited evaluations. Moreover, our results suggest that luxury hotel brands might do more to meet consumers expectation in social media, by focusing specifically on image (visual data) analytics. In this way, the present study provides a clear example of how to reply to the previous recommendations on monitoring social media though new approaches based on machine learning algorithms.

Given the strong effects of consumers' online evaluations of brands on successful brand strategies (Lee et al., 2012), marketers are further advised to include the features that are more able influence consumers' perception of the quality of the hotel as: dinner table, bathroom, double bed, washbasin, living room and restaurant. Thus, luxury hotel brands should try to strengthen their strategies, especially online, by including more visually appealing contents based on the above mentioned features. This process would return into building better brand impressions for consumers, and to engage them more through social media brand posts. For instance, hotel managers should take into consideration the larger interest of tourists on interior elements of the hotel rather than on the exterior ones (i.e., building, view, etc.), which should be echoed in the branding campaign in social media and other channels. Furthermore, brand and hotel managers can compare and contrast our results with their actual campaign, to have a preliminary evaluation of the effective match between what consumers stress in their pictures and what managers underline in their marketing campaigns.

Finally, the adopted methodology might be considered as a technique for a "dimensionality-reduction" of the volume of "big" visual data, while opening up the potential for visual consumer research methods as never exploited before. Indeed, the usage of a machine learning algorithm allows the systematic screening of images, in

Table 2
The most recurrent elements in the pictures taken in the six luxury hotels.

	bedroom	dinner table	bathroom	double bed	living room	restaurant	washbasin	person
hotel 1	48	9	31	9	51	0	11	0
hotel 2	67	32	41	0	0	0	47	0
hotel 3	37	34	16	17	42	16	11	12
hotel 4	8	6	5	9	0	9	6	4
hotel 5	171	91	95	66	74	61	0	44
hotel 6	128	152	36	38	63	106	0	46
MEAN	76.50	54.00	37.33	23.17	38.33	32.00	12.50	17.67
SD	55.88	51.94	28.52	22.48	28.85	39.05	16.07	19.75

opposite to the human observers who might look at much smaller numbers (Rose & Willis, 2019). In this way, our research overcomes the constraint of the manual analysis conducted on a few hundred images at most (Rose & Willis, 2019).

Summarizing, the analysis of visual elements of consumers' unsolicited communication in terms of photographs provides (i) original insights into consumers' experience, (ii) a favored channel to access consumers' feeling about their experience, (iii) a deeper understanding of consumers' thoughts, (iv) support to transform the insights into new effective brand (hotel) experience, and (v) improvements in the communications from the hotel to consumers. In other words, managers would be able to improve the way of communicating the brand through more effective images, which might turn into a larger appreciation of the hotel characteristics and services, and ultimately in the enhanced experience. These elements would strongly contribute to the delivery of a holistic consumer's experience (Schmitt, 1999, 2003).

7. Limitations and future works

Despite the implications for scholars and practitioners, the present research also involves some limitations to be taken into account. First, the adopted methodology involved the collection of pictures shared online through one tourism specific platform like TripAdvisor, without considering the positive or negative text associated with each picture. Thus, findings summarize the importance of such elements of luxury hotel in the consumption experience without providing any measure of the weight of the positive or negative factor in the evaluation of the overall experience. Further studies can use our research as a starting point to investigate if the pictures shared online are related to positive or negative experiences (simultaneously evaluating the image and the associated text), and the major influence of certain elements by combining the pictures analysis with the content analysis of the text associated with them. Similarly, considerations about the external elements could be investigated in future studies to figure out which ones play an attractive or detractive role. Moreover, a comparison with other specialized (i.e., Booking) and not specialized social media platform (i.e., Instagram) would provide more generalizable results. For instance, analyzing images from different social media would help to understand also the circulation route (in terms of number of people shared/retweets, etc.).

Secondly, the choice of six hotels in a very specific geographic context (London, UK) and one platform (TripAdvisor) leading to the collection of 7,395 is another limitation that need to be acknowledged. Future works might build a larger data set with hotels in other cities with similar characteristics. Likewise, the present study is focused on luxury hotels only, new studies could investigate the most important elements emerging in the case of budget hotels. Since budget hotels and budget hotel chains (i.e., Premier Inn, Ibis, etc.) mean lower prices but not necessarily lower quality (i.e., cleaning service), studies might compare our results with this hotel category in order to understand if the most important visual elements transcend the luxury experience to embrace a broader tourism experience. Also, new research can triangulate the data with information about the duration of the vacation that might impact the consumption experience in terms of perception of quality and service (i.e., will a short break stress more the appeal of such elements of a luxury/budget hotel?). Indeed, a different length or purpose of the vacation might impact on the more eye-catching elements of the hotel, as well as the view/panorama from the hotel might play a role only for a certain category of tourists (i.e., food lovers VS eco-tourists).

Finally, since the methodology is based on the usage of a machine learning algorithm provided by Wolfram Mathematica software, the percentage of error in correctly classifying (recognizing) the different objects in the pictures is strictly related to the advancements in computers science and mathematics, thus comparing the results through other software (i.e., *R*) or machine learning algorithms would

corroborate the reliability of the results.

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