The influence of cultural origins of visitors when staying in the city that never sleeps

Sérgio Moro[1,*]
Paulo Rita[2]
Pedro Ramos[1,3]
Joaquim Esmerado[1]

Abstract

Smart tourism can benefit from Big Data to offer personalized services that better meet tourist demands. This study addresses the adaptation versus globalization debate by analyzing all reviews made about New York City (NYC) on Booking.com, a total of 115,297 reviews for 307 hotels. The collected dataset was divided into 10 cultural clusters and category of each hotel by the star rank system. Then, 5 categories were analyzed: cleanliness, food, location, price, and staff.

Results showed both divergent and convergent opinions about the accommodation offer of NYC, depending on the selected category. Food and staff gathered different opinions among the 10 cultural clusters. Particularly, cultures less subjected to globalization tend to write more negative reviews about food. Also, cultures with a higher distance in treatment between tourists and staff such as Confucian, South-East Asia and Middle-Easterners, appreciate less the egalitarian treatment of NYC hotel staff.

Keywords

Culture; tourist satisfaction; online reviews; social media; New York; NYC.

---

[1] Instituto Universitário de Lisboa (ISCTE-IUL), ISTAR-IUL, Lisboa, Portugal
[2] NOVA Information Management School (NOVA IMS), Universidade Nova de Lisboa, Campus de Campolide, 1070-312 Lisboa, Portugal
[3] Instituto Universitário de Lisboa (ISCTE-IUL), IT-IUL, Lisboa, Portugal
* Corresponding author. E-mail: scmoro@gmail.com

1. Introduction

Today's world is driven by data, and decisions made based on information gathered from online platforms, whether at a consumer or corporate level. The Internet has exponentially grown with the Web 2.0 by adopting a consumer-generated content paradigm where users are empowered by the flow of information as both producers and consumers (Amado et al., 2018). Several types of social media platforms have been developed to offer increasing information exchange capabilities meeting users' demands (Gandomi & Haider, 2015). As a result, social media is a major contributor to a trend coined as Big Data, where data keeps coming at tremendous speed and volumes, and needs to be quickly handled and used (Canito et al., 2018). The tourism and hospitality industry is no exception: it has been a pioneer through some of the first online review platforms, including TripAdvisor, and it has also taken advantage of generic social networks such as Facebook via advertising as well as business posts (van der Hoeven, 2019). Tourism researchers have acknowledged adoption by managers of such media for leveraging decision making (Moro et al., 2017).

Big Data does not hold significant value in itself, but only after harvesting and harnessing it through data analytics techniques capable of dealing with the large volumes that its true value emerges (Chen et al., 2012). Big Data can be included in the spectrum of information and communication technology (ICT) breakthroughs which have been adopted in tourism, leading to a new trend called smart tourism (Gretzel et al., 2015). Smart tourism represents the stepping stone toward an evolution from traditional to electronic tourism, where technology goes hand-in-hand with tourism to offer more focused tourism services that assist in better serving each tourist. Although we live in a globalized world fueled by both planetary transportation and ICT infrastructures, the "one model fits all" has proven ineffective in general, and particularly in the tourism and hospitality industry (Francis-Lindsay, 2013). Thus, the large volumes of Big Data enable to extract insightful knowledge for more segmented services, helping hoteliers to provide personalized services based on the origins of tourists, which may ultimately lead to an improvement of customer satisfaction.

This study offers a broad perspective of the hotel offer in New York City (NYC) from the point of view of foreign visitors to the United States. It is grounded on 115,297 customer reviews posted between 2016 and 2018 in Booking.com. Specifically, the cultural perspective is analyzed under 5 categories according to Prayag and Ryan (2011) for cleanliness, and to Calheiros et al. (2017) for the remaining: food, location, price, and staff. Through visually appealing heat matrices, the purpose of this study is to understand how countries of origin and respective embedded cultures influence tourists perceptions reported in reviews, including the hotel category (i.e., number of stars' rank). The development of cities with transnational roles demand adaptation on how they represent themselves to tourists (see: Maitland, 2012), even more so if visitors come from different generating countries. Thus, this study contributes to the globalization versus adaptation debate in tourism by assessing how the cultural differences between guests and host destination (NYC) influence tourists' comments. Findings can help hoteliers to offer personalized services according to travelers' nationalities, in order to improve customer satisfaction and subsequent word-of-mouth.

2. Background

2.1. The cultural origins of visitors' influence in tourist satisfaction

Culture has been examined in terms of how explicit manifestations of culture are related to the attractiveness of a city (Ferilli et al., 2015) as well as regarding travel motivations and desired activities within destinations (Rita et al., 2018; Moro, 2020). The antecedents of place attachment within the context of cultural tourism destinations were investigated by Hou et al. (2005) who specifically examined tourists with different cultural backgrounds and found that the meaning and formation of attachment may differ depending on the ethnic background of tourists.

Literature has also reported the impact of cultural background on image formation (McCartney, 2008) as well as that plural destination image perceptions exist due to the variety of cultures represented by target market countries (MacKay & Fesenmaier, 2000). Furthermore, cultural distance between 2 places may influence the manner in which tourists from a target market view the tourist destination, with cultural proximity found by Huang et al. (2013) to be the most significant predictor of travel intention.

Hjalager (2007) draws attention to the different manifestations of the globalization of the tourism industry, highlighting that "practical outcomes are unevenly distributed across enterprises, countries, and regions" (p. 452). In fact, the tourism movements contribute to globalization by facilitating intercultural contact (Cleveland et al., 2016). However, cultural roots at isolated destinations can help hosts to adapt their tourism services by promoting their unique local culture, in a simultaneous effort of preserving culture in the long term by benefiting from the tourists' demand for cultural uniqueness (Tolkach & Pratt, 2019). On the opposite, one might think that destinations largely exposed to intercultural exchange such as NYC may lead to lesser need to adapt to guests. As Moro (2020) found out, that is not the case, at least for the gambling American and Asian centers of Las Vegas and Macau, respectively. Indeed, guests' satisfaction varies depending on their cultural origins (de Carlos et al., 2019).

2.2. Big Data analytics applied to social media in tourism and hospitality

Computerized data analytics approaches still hold some limitations in identifying the subtle semantic differences (Matthes & Kohring, 2008), since a computer analytical program cannot discern the subtle differences in the meaning of words and can only count the frequency of keywords, and Kim et al. (2016) noted precisely that when analyzing TripAdvisor reviews. However, text mining is developing to mitigate such limitations (Wei et al., 2015), and the future is promising in a data-driven world where tons of data keep piling up (Hashem et al., 2015). Moreover, for large volumes of data a manual analysis such as the one conducted by Kim et al. (2016) renders unfeasible. Ahn et al. (2017), Lee et al. (2017) and Xiang et al. (2017) noted precisely that when analyzing volumes of the order more than 10,000.

In the last 5 years, studies applying big data analytics to social media data within the realm of tourism have emerged (Table 2). Wood et al. (2013) estimated visitation rates of world recreational sites, based on the locations of photographs in Flickr, and derived travelers' origins, based on the information from the profiles of the photographers, and concluded that the crowd-sourced information was a reliable proxy for empirical visitation rates. In turn, Miah et al. (2017) used also geotagged photos uploaded by tourists to Flickr to analyze and predict behavior patterns of tourists at specific destinations. By following a design science research approach, these authors developed an artefact and demonstrated a method for analyzing unstructured big data to support strategic decision-making in tourism destination management.

Furthermore, Marine-Roig and Clavé (2015) investigated the online image of Barcelona by performing big data analytics on more than 100,000 travel blogs and online reviews written by tourists who visited the city within a decade. They argued that positioning strategies and brand management of destinations can be improved by applying business intelligence to user-generated content.

The social network juggernaut, Facebook, one of the top 3 global sites in the world and accounting for over 2 billion people, can also be used to generate consumer engagement and promote tourist destinations. In fact, Mariani et al. (2016) applied big data analysis to the Facebook pages of regional Destination Management Organizations (DMOs) and found that user engagement received positive impact from visual content (e.g., photos) and moderately long posts but negative impact from high post frequency and morning posts. Moreover, Del Vecchio et al. (2017) derived patterns and opportunities of value creation for a Smart Tourism Destination generated by Big Data in tourism. Specifically, their findings supported arguments favoring improvement of decision-making, development of marketing strategies with more personalized offerings, transparency and trust in dialogue with customers and stakeholders, and emergence of new business models.

Data from the world´s known social networking and microblogging service Twitter was used to analyze tweets by commercial, news/blogs and private user groups regarding cruise travel (Park et al., 2016). As expected, words related to travel, destination, industry, and emotion were most frequently used in composing tweets. Interestingly, celebrities, professional bloggers, cruise lines, and travel agencies were at the forefront of major subgroups on cruise topics on Twitter. Furthermore, the Chinese microblogging website Sina Weibo, already one of top twenty most used sites worldwide, was used to examine the behaviors of Chinese tourists in Switzerland (Liu et al., 2017) in order to address questions about Chinese travelers such as their profiles, trends in keywords, and differences between first time and repeat visitors.

In researching online travel forums, Edwards et al. (2017) found that the knowledge-sharing structure was actually developed by community residents who showed disguised as local experts and served as ambassadors of a tourist destination. However, the available collective intelligence in those forums counted with tourists as co-producers.

Finally, one needs also to account for the risks/drawbacks/limitations of using big data analytics, such as scalability and storage issues, timeless of analysis, and representation of heterogeneous data (please refer to Bhadani & Jothimani, 2016, for further discussion).

2.3. New York City hospitality unveiled through social media

According to the market research firm Euromonitor (2019), New York is one of the most visited cities in the world, hosting 14 million international visitors, and consequently being placed in the top 10 ranking worldwide, despite the fact that 77% of the top 100 are either Asian or European city destinations. By adding the 17 million domestic visitors it received (Statista, 2018), New York City (NYC) totaled over 30 million tourists in a single year. This figure is higher than most whole countries in the world are able to achieve.

Tourism exerts an important economic impact in New York (Currid-Halkett & Stolarick, 2010). Traveler spending reached more than USD 68 billion, and even generated USD 109 billion in total business sales, including indirect impacts. 764,000 jobs were sustained by tourism activity, accounting for 8.2% of all New York employment, placing tourism as the 4th largest employer in New York (Tourism Economics, 2017). Travel spending by sector shows lodging leading, followed by food service, transport, retail, and recreation.

A number of studies have recently focused on characterizing New York City as a tourist destination using a consumer perspective via data collected from social media platforms (Table 1) arguing that these have become major information sources for both customers and managers.

Based on Herzberg's (1958) 2-factor theory, Kim et al. (2016) analyzed online reviews from TripAdvisor and showed that most satisfiers were distinct from dissatisfiers in full-service hotels, although "staff and their attitude" and "service" were common in limited-service hotels, with the former being considered the most critical factor.

Rose and Blodgett (2016) set up a quasi-experimental design involving planning a trip to NYC and studied the impact of service failure and recovery on reputation management via online reviews. Empirical findings showed that when the ratio of negative to positive reviews attributed to controllable factors became greater, hotel reputation was adversely affected, and management responses could mitigate the adverse effects of negative reviews. Furthermore, Lee et al. (2017) demonstrated that negative online reviews and emotional expressions played a more crucial role in consumers' information processing and decision-making. Specifically, negative reviews were actually considered to be more helpful than positive ones, when potential customers were reading online hotel reviews for their future stay. Interestingly, negative emotions associated with high intensity provoked a reduction in their degree of helpfulness.

There is a clear trend towards working with increasing volumes of data to perform social network analysis, SNA (e.g., Kim & Hastak, 2018) by examining social ties and network structure in social networks (e.g., Luo & Zhong, 2015). Recently, hotels of NYC showed discrepancies in their representation across online review platforms, whereby Xiang et al. (2017) applied machine learning and text analytics to 820,778 reviews to measure information quality through linguistic and semantic features, sentiment, rating and usefulness of those reviews.

The effects of different traveling groups (couples, friends, family, solo, and business) experiences on travelers' satisfaction rating for hotels in which they stayed were investigated in NYC hotels through the application of text analytics to more than 100,000 reviews (Ahn et al., 2017). Whereas the highest satisfaction with the hotel they chose were expressed by couples, the lowest satisfaction levels were shown by business groups.

The fact that NYC is a cosmopolitan metropolis may raise important cultural issues for newcomers with origins in distinct cultural places. The cultural diversity of tourism industry employees can lead to different guests' perceptions about the same employee, depending on the guest's origin (Moro, 2020). This is widely acknowledged in existing literature focused on foreign labor in NYC (e.g., Bao, 2001; Kuba, 2019). However, no study has yet attempted to understand the point of view of tourists visiting NYC. Additionally, most of the adopted approaches are based on data directly collected through questionnaires/surveys, limiting the number of responses and possible bias due to the difficulty in choosing a representative sample of the population (Moro, 2020). In contrast, we use a large sample of online reviews which are currently the most widely adopted method within tourism for guests to provide feedback within their stay at a destination. While the study by Moro (2020) unveiled that the cultural differences between guests and host destination result in different levels of satisfaction expressed in online reviews for the cities of Las Vegas and Macau, the specific context of both major gambling destinations does not allow to generalize the results to NYC, as the above cited author mentions in his study's limitations.

3. Materials and methods

The Big Data required for the experiments was collected from Booking.com, which is an e-marketplace where travelers search and purchase the best possible offers for their travels (Moro et al., 2018). Through this platform, it is possible to book hotels, flights, or rent cars. Since this study focused on the stay experience, only NYC hotels were considered. To match competition, Booking.com has incorporated an online review service where travelers can write about their experiences. Specifically, a traveler has 2 possible choices to freely provide negative and/or positive feedback. Such feature helps readers to clearly know about which aspects that specific traveler liked or disliked the most. Thus, it avoids the need to adopt a sentiment analysis tool to extract sentiment polarity which, despite recent advances, still holds limitations (Lin et al., 2018). Additionally, travelers' nationalities were collected to categorize their cultural origins. The initial dataset consisted of 211,327 reviews collected through a specifically web scraping script developed in R using the "rvest" package.

Figure 1 shows the undertaken procedure. After retrieving the reviews, the dataset was filtered by country, and all the United States homeland visitors to NYC were excluded, leaving a total of 115,297 foreign visitors' reviews. These numbers show the international recognition of NYC, one of the most known city brands, with more than half of reviews written by visitors coming from abroad. Table 3 exhibits the counters for the information retrieved, as well as the average Booking.com score per hotel category (i.e., number of stars rank). Since there was only one hotel ranked 1-star, it was included in the 2-star rank, in a "1 or 2" category encompassing the lower ranked hotels. Higher ranked hotels tend to receive higher scores, meaning that these hotels are meeting the usually higher expectations of their more demanding tourists. The NYC offer on Booking.com includes a total of 307 hotels, from which the middle ranked 3 and 4-star hotels represent the majority. The numbers highlight the diversity of NYC offer.

As stated above, this study aims to understand the influence of the cultural perspective on the tourists' perceptions. Consequently, based on each reviewer's country of origin, the cultural cluster was computed considering the classification proposed by Mensah and Chen (2013). The 10 considered cultures are shown in Table 4, as well as some of the countries associated with each culture (the remaining ones were omitted to save space). Table 5 shows the number of reviews collected per culture and star category.

The specific characteristics of hotels which guests mention and evaluate are usually comprised of only a handful of categories. For the present study, 5 categories were considered: cleanliness, food, location, price, and staff. These categories were chosen based on the studies by Prayag and Ryan (2011) for cleanliness, and by Calheiros et al. (2017) for the remaining features. The procedure consisted in parsing each negative text field for every review and validate if any term related to each of the 5 categories occurred within the text. If it did, then a -1 score was granted for that category (it was accounted only once, even if it was mentioned more than once). Likewise, the same procedure was applied for the positive text field, but considering instead a positive +1 score. If, for a given category, text was mentioned in both the negative and positive fields, the overall score canceled itself to 0 (zero). If no term occurred for a category, the score for that category was also set to 0 (zero). It should also be noted that a review may have only negative text, or only positive text. Nevertheless, the categories were matched within the text in a percentage of 17% (price) to 56% (location) of the total of 115,297 reviews (Table 6). A sample of the terms considered for each category is shown in Table 7. Those terms were drawn from the abovementioned studies. Next, an example is shown to illustrate the computations that were made. For the review with the following texts (in **bold** the considered keywords):

> *Negative ("cons"): When I asked for an upgrade to have a view I got a room on floor 28 but still didn´t have a great **sight**. Also there was a problem with the **buffet** at the **restaurant**.*
>
> *Positive ("pros"): The **breakfast** was excellent.*

the score for location is -1, and for food is 0 (zero), since the positive reference to breakfast is cancelled by the negative claims about the buffet. For the remaining categories, i.e. cleanliness, price, and staff, the score is 0 since they were not mentioned in the review.

4. Results

The results are shown in the form of heat matrices, one per each of the 5 categories. The 2 dimensions of each matrix are the cultural cluster and the hotel star rank. This helps in providing through a simple picture how the culture influences the relevance given by guests to certain aspects in online reviews, mediated by the star system. Each cell ranges from white to black in a gray scale, with white representing a negative perception, and black a positive one. The cell background is computed from the average score ($\overline{x}$) of each review individual score per category, as previously explained. To show values of dispersion per culture and star rank, the standard deviation (σ), computed in percentage through the STDEV.P Microsoft Excel formula, is also exhibited.

Figure 2 exhibits the 5 matrices for each category, including metrics per culture and hotel star rank. Per line of each matrix, i.e., per culture, the average sentiment score is computed as explained in Section 3, as well as the standard deviation. Regarding cleanliness, there is significant dispersion (around 8-10%) for most cultures across the four hotel categories, while the average sentiment remains stable (0.113-0.199) for all cultures except the Latin American, who show the lowest sentiment (0.084) and the highest dispersion (11.7%). As for the analysis per hotel star category (matrix columns), the 3-star units are the ones that received the most positive feedback about cleanliness (0.264). In respect to food, the expressed sentiments are heterogeneous among the cultures, especially for the lower ranked (less stars) hotels, with the Germans praising 1-2-star units, while the Nordics and South-East Asians favoring 5-star units. Furthermore, the former (Germans) and South-East Asians are the ones where the divergence among the different categories (with σ above 7%). The location is in general appreciated by all cultures (average sentiment score of 0.369 to 0.416), particularly by the Confucian (0.416) and South-East Asians (0.411). As for the price, while there is dispersion across cultures (σ of 3.4% to 6.9%), the high σ together with the gray shades of the corresponding matrix enables to understand that guests particularly dislike the high prices of 4 to 5-star hotels.

5. Discussion

In a global perspective, the data collected provides evidence of the homogeneous positive satisfaction feedback regarding the location of hotels, independently from the hotel rating or the cultural background of the reviewers (standard deviation near zero). In fact, location is the best rated category, which can be justified by the urban characteristics of NYC which favor a convenient location of a great number of its hotels relative to the city's points of interest, avoiding mobility constraints due to traffic jams (Faghih-Imani et al., 2017).

Price is the only category that consistently denotes a negative feedback for all hotel ranks and cultures. In fact, hospitality literature acknowledges that price has a negative impact on the perceived value (Oh, 1999) that is unveiled in online reviews (Ye et al., 2014). The negative perspective on price is consistent with the fact that NYC is one of the most expensive cities in terms of accommodation, given its high land cost (Himmelberg et al., 2005). However, the price heat-matrix (Figure 2) shows that the level of satisfaction tends to highly vary inversely with respect to the hotel's number of stars, with all cultures concurring to a higher dissatisfaction level for higher rated hotels. In fact, the standard deviation is the highest for all cultures among the 5 categories, showing that travelers are not recognizing enough value for premium hotels to justify their higher prices. This result is consistent with the study by Ye et al. (2014). Our study contributes to existing literature by unveiling that this is indeed a cross-cultural effect.

The food category is characterized by having on average a neutral customer opinion (neither positive nor negative). However, there is considerable dispersion in the data (difference between maximum and minimum, and the standard deviation) which can be interpreted as reviews being distant from an unanimous opinion. Furthermore, this happens for both hotel star rank as well as for cultures.

Generically, cleanliness and staff show mostly positive ratings but some dispersion can be observed in the results. Figure 3 shows the dispersion for all hotel star ranks per culture, grouped by category, through boxplots, where the cross denotes the average, and the middle line corresponds to the median. It confirms that for location, cultural differences have no perceivable relevance. This can be justified due to the high density of the city of NYC area (Baum & Mezias, 1993; Fainstein & Stokes, 1998). Moreover, "urban tourism" is characterized by a high concentration of hotels nearby cities' attractions exactly because hoteliers are aware of the advantages of having their hotels located close to those attractions (Luo & Yang, 2016). Concerning price, the most negative evaluations are associated with visitors from Africa, Middle East and South-East Asia. Accordingly, cultures associated with less affluent regions tend to show a more negative opinion on price (Table 8, wealth by culture). In the price heat-matrix (Figure 2), one can observe that visitors from African and South-East Asia are those who better rate lower range hotels, showing higher discrepancy between low range and midscale/premium hotels.

Relative to food, lower ratings are collected from visitors from Africa, Middle East and South-East Asia. The globalization level index shows evidence that populations from Africa, Middle East and South-East Asia are among the 4 cultures least subjected to globalization (Table 9) which can help explaining the achieved results. However, while Latin America is the cultural region considered as the least globalized, visitors from that part of the world tend to rate food positively whereas visitors from Eastern Europe tend to evaluate food negatively in spite of their strong globalization index. There is a large percentage of Latin American immigrants working in NYC hotels and restaurants since the early 1990s (Waldinger, 1992), which may contribute to influence New York's supply in the domain of food in terms of menu offerings. A study by Chadee and Mattsson (1996) suggests that Asians tend to be more demanding than Europeans when it comes to the food and beverage industry. Our results show that there has been a trend towards unification in this domain, over 2 decades later of the abovementioned study. As such, the results obtained for the Anglo-Saxon, Eastern European, German and Confucian origin countries are nowadays not very far apart, supporting claims of a globalization trend.

Concerning cleanliness, the least positive evaluation comes from the cultures associated with Latin America, Middle East and Africa, while the most positive ones are from

Anglo-Saxon, Nordic and Confucian cultures. The study by Banerjee and Chua (2016) highlights that guests complain about lack of cleanliness in American hotels, while dirtiness is not mentioned for the hotels they studied located in Middle East, Africa, and Asia Pacific. Our result may denote that travelers originated in those regions are used to a better cleanliness service in their home countries and thus are more sensitive to cleanliness issues, reflecting their opinions in online reviews, as it was found by both our study and the one by Banerjee and Chua (2016).

As to the staff category, the lowest evaluation emerges from visitors from Confucian, South-East Asia and the Middle-East cultures. It is possible that the cultures least influenced by values from western countries tend to react less positively to the employees' standards in New York. This is in line with Chen and Pizam (2006, p. 192), who indicated that "… in relatively large power-distance countries such as China and India, hospitality customers come from higher status strata of the population and expect an elevated level of service from hospitality service employees who most likely come from people with a lower social status. This contrasts with more egalitarian services provided by hospitality employees in the Western cultures where the difference between the employees and guest is often not noticeable". The tourists from those cultures do not seem to value positively a tone of greater proximity generated in their interactions with hospitality staff in New York.

This study's findings provide evidence that differences between cultures are not so extreme, and can be justified by the fact that the United States is a nation built from recent immigrants which entails a greater globalization factor, including at the level of tourism (Wilson, 2008). This also causes tourists who look for NYC to be better identified with every hotel, since those in turn frequently employ multicultural staff, as it was pointed out by Jafari and Way (1994) in a study on the United States. Additionally, according to Heo et al. (2004) that factor was pivotal due to the strong competition. The latter factors tend to make tourists feel closer to the general entourage and makes the cultural factor less prominent, and as such attenuates any sense of cultural shock due to perceived more proximity between guests and staff.

Regarding the globalization versus adaptation debate, the achieved results for NYC differ from the ones presented by Moro (2020) for Las Vegas and Macau. While both gambling cities are renowned tourism destinations, the staff in tourism units is more linked to local workers when compared to NYC (Moro, 2020). Hence, the adaptation of NYC results from the multicultural available workforce that attenuates the cultural differences to guests (Jafari & Way, 1994).

6. Conclusions

The value of Big Data lays on using its volume to offer personalized solutions to real-world problems by using pattern-driven approaches (Zhou et al., 2016), and Big Data in smart tourism is no exception. In this study, we aimed to contribute to the adaptation versus globalization debate in tourism. Specifically, we extracted from Booking.com all the reviews made by foreigners visiting NYC to understand patterns of behavior in travelers' satisfaction considering cultural clusters. Social media has the power to offer Big Data, and the result was a total of 115,297 reviews for 307 hotels. 5 categories were analyzed: cleanliness, food, location, price, and staff. The data collected was then divided into cultural clusters, and also hotels' star rank, to partition the reviews into logical categories.

Smart tourism is about using technology to offer personalized services to tourists. In this case, some interesting findings emerged that can help to shape hotels' offer to better meet tourists' demand. The main findings showed foreign travelers had both divergent and convergent opinions of the accommodation offer of the renowned and globalized NYC, depending on the category they belonged to. Hotels' location was not only the category about which reviewers showed they were pleased the most, but also this result was homogeneous across cultures. The large concentration of hotels and attractions in a small and densely populated area helps to explain such finding. On the opposite side, food and staff were the 2 categories where the results diverged the most among the analyzed cultural clusters. Regarding food, the clusters least subjected to globalization were the ones that criticized the most hotels' food, namely Africa, Middle East and South-East Asia. The cultures which mentioned more negatively hotels' staff were those that appreciated less an equal treatment between staff and customers. Thus, the results for NYC were supported by literature devoted to globalization. Price was negatively classified by all cultures, particularly in higher rated 4 and 5-star hotels.

The findings stemming from this study lead to practical recommendations for hotel unit managers. The multicultural labor market of NYC reflected in tourism human resources should continue to be fostered as it has revealed an important asset of hotels. Further, there should be some cautiousness especially of large chains (Moro et al., 2020) when investing in acculturated training strategies that may limit the ethnical diversity that has been fruitfully recognized by NYC guests. The food delivered by NYC hotels should be a subject of further attention by managers. The typical continental buffet served in most breakfasts may be one of the reasons that led to guests with distinct cultural backgrounds (Africa, Middle East and South-East Asia) to signal food in the “cons” text area. Managers can start diversifying their offer to meet distinct cultural habits. Additionally, although Western cuisine has been gradually enriched through the globalization effect by incorporating food from culturally distinct nations (e.g., Chinese and Japanese), more effort can be made to include lesser known to Westerners food.

This study has limitations that need to be clarified. First, this study is focused on NYC, one of the most known and prized brand destinations, with several specificities. Thus, the results cannot be generalized. Notwithstanding, this approach can be directly replicable to any other context. Also, this study is entirely dependent on the available data, i.e., on what guests mention in their reviews. Thus, from this study, it remains unclear the guests’ points of view about not mentioned categories - we can only say that those categories did not deserve attention enough from the guest to write about them. Another limitation related to the coding procedure followed is the assumption that the guest always writes positive aspects on the “pros” text box and the negative ones on the “cons” box.

References

Ahn, D., Park, H., & Yoo, B. (2017). Which group do you want to travel with? A study of rating differences among groups in online travel reviews. *Electronic Commerce Research and Applications*, 25, 105-114.

Amado, A., Cortez, P., Rita, P., & Moro, S. (2018). Research trends on Big Data in Marketing: A text mining and topic modeling based literature analysis. *European Research on Management and Business Economics*, 24(1), 1-7.

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

Bao, X. (2001). *Holding Up More Than Half the Sky: Chinese Women Garment Workers in New York City, 1948-92*. University of Illinois Press.

Baum, J. A., & Mezias, S. J. (1993). Competition, institutional linkages, and organizational growth. *Social Science Research*, 22(2), 131-164.

Bhadani, A. K., & Jothimani, D. (2016). Big data: challenges, opportunities, and realities. In Effective Big Data management and opportunities for implementation (pp. 1-24). IGI Global.

Calheiros, A. C., Moro, S., & Rita, P. (2017). Sentiment classification of consumer-generated online reviews using topic modeling. *Journal of Hospitality Marketing & Management*, 26(7), 675-693.

Canito, J., Ramos, P., Moro, S., & Rita, P. (2018). Unfolding the relations between companies and technologies under the Big Data umbrella. *Computers in Industry*, 99, 1-8.

Chadee, D. D., & Mattsson, J. (1996). An empirical assessment of customer satisfaction in tourism. *Service Industries Journal*, 16(3), 305-320.

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: from big data to big impact. *MIS Quarterly*, 1165-1188.

Chen, P. J., & Pizam, A. (2006). *Cross-cultural tourism marketing*. Tourism Management Dynamics, Trends, Management and Tools. Oxford: Elsevier Butterworth, 187-195.

Cleveland, M., Rojas-Méndez, J. I., Laroche, M., & Papadopoulos, N. (2016). Identity, culture, dispositions and behavior: A cross-national examination of globalization and culture change. *Journal of Business Research*, 69(3), 1090-1102.

Currid-Halkett, E., & Stolarick, K. (2010). Cultural capital and metropolitan distinction: Views of Los Angeles and New York. *City, Culture and Society*, 1(4), 217-223.

de Carlos, P., Alén, E., Pérez-González, A., & Figueroa, B. (2019). Cultural differences, language attitudes and tourist satisfaction: a study in the Barcelona hotel sector. *Journal of Multilingual and Multicultural Development*, 40(2), 133-147.

Del Vecchio, P., Mele, G., Ndou, V., & Secundo, G. (2017). Creating value from Social Big Data: Implications for Smart Tourism Destinations. *Information Processing & Management*. DOI: 10.1016/j.ipm.2017.10.006.

Edwards, D., Cheng, M., Wong, I. A., Zhang, J., & Wu, Q. (2017). Ambassadors of knowledge sharing: Co-produced travel information through tourist-local social media exchange. *International Journal of Contemporary Hospitality Management*, 29(2), 690-708.

Euromonitor (2019) *Top 100 City Destinations*. Euromonitor International. London, UK.

Faghih-Imani, A., Anowar, S., Miller, E. J., & Eluru, N. (2017). Hail a cab or ride a bike? A travel time comparison of taxi and bicycle-sharing systems in New York City. *Transportation Research Part A: Policy and Practice*, 101, 11-21.

Fainstein, S. S., & Stokes, R. J. (1998). Spaces for play: The impacts of entertainment development on New York City. *Economic Development Quarterly*, 12(2), 150-165.

Ferilli, G., Sacco, P. L., & Noda, K. (2015). Culture driven policies and revaluation of local cultural assets: A tale of two cities, Otaru and Yūbari. *City, Culture and Society*, 6(4), 135-143.

Francis-Lindsay, J. (2013). From fashion to “tangible-intangible” action: local communities “culturizing” new tourism development. *WIT Transactions on State of the Art in Science and Engineering - Tourism as a Tool for Development*, 4, 11-22.

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, 35(2), 137-144.

Gretzel, U., Sigala, M., Xiang, Z., & Koo, C. (2015). Smart tourism: foundations and developments. *Electronic Markets*, 25(3), 179-188.

Hashem, I. A. T., Yaqoob, I., Anuar, N. B., Mokhtar, S., Gani, A., & Khan, S. U. (2015). The rise of “big data” on cloud computing: Review and open research issues. *Information Systems*, 47, 98-115.

Heo, J. K., Jogaratnam, G., & Buchanan, P. (2004). Customer-focused adaptation in New York City hotels: exploring the perceptions of Japanese and Korean travelers. *International Journal of Hospitality Management*, 23(1), 39-53.

Herzberg, F. Mausner, B., & Snyderman, B.B. (1958). *The Motivation to Work*. Transaction Publishers, New Brunswick, New Jersey. Originally published in 1959 by John Wiley & Sons, Inc.

Himmelberg, C., Mayer, C., & Sinai, T. (2005). Assessing high house prices: Bubbles, fundamentals and misperceptions. *Journal of Economic Perspectives*, 19(4), 67-92.

Hjalager, A. M. (2007). Stages in the economic globalization of tourism. *Annals of Tourism Research*, 34(2), 437-457.

Hou, J. S., Lin, C. H., & Morais, D. B. (2005). Antecedents of attachment to a cultural tourism destination: The case of Hakka and non-Hakka Taiwanese visitors to Pei-Pu, Taiwan. *Journal of Travel Research*, 44(2), 221-233.

Huang, W. J., Chen, C. C., & Lin, Y. H. (2013). Cultural proximity and intention to visit: Destination image of Taiwan as perceived by Mainland Chinese visitors. *Journal of Destination Marketing & Management*, 2(3), 176-184.

Jafari, J., & Way, W. (1994). Multicultural Strategies in Tourism. *Cornell Hotel and Restaurant Administration Quarterly*, 35(6), 72-79.

Kim, J., & Hastak, M. (2018). Social network analysis. *International Journal of Information Management*, 38(1), 86-96.

Kim, B., Kim, S., & Heo, C. Y. (2016). Analysis of satisfiers and dissatisfiers in online hotel reviews on social media. *International Journal of Contemporary Hospitality Management*, 28(9), 1915-1936.

Kuba, A. (2019). Migration and wage labour: a case study of Ghanaians in New York City, 1957-2010. *International Journal of Migration and Residential Mobility*, 2(1), 56-82.

Lee, M., Jeong, M., & Lee, J. (2017). Roles of negative emotions in customers' perceived helpfulness of hotel reviews on a user-generated review website: a text mining approach. *International Journal of Contemporary Hospitality Management*, 29(2), 762-783.

Lin, B., Zampetti, F., Bavota, G., Di Penta, M., Lanza, M., & Oliveto, R. (2018). Sentiment Analysis for So ware Engineering: How Far Can We Go?. *Proceedings of the International Conference on Software Engineering (ICSE'18)*, May 27-June 3, Gothenburg, Sweden. ACM.

Liu, Z., Shan, J., Balet, N. G., & Fang, G. (2017). Semantic social media analysis of Chinese tourists in Switzerland. *Information Technology & Tourism*, 17(2), 183-202.

Luo, H., & Yang, Y. (2016). Intra-metropolitan location choice of star-rated and non-rated budget hotels: The role of agglomeration economies. *International Journal of Hospitality Management*, 59, 72-83.

Luo, Q., & Zhong, D. (2015). Using social network analysis to explain communication characteristics of travel-related electronic word-of-mouth on social networking sites. *Tourism Management*, 46, 274-282.

MacKay, K. J., & Fesenmaier, D. R. (2000). An exploration of cross-cultural destination image assessment. *Journal of Travel Research*, 38(4), 417-423.

Maitland, R. (2012). Capitalness is contingent: tourism and national capitals in a globalised world. *Current Issues in Tourism*, 15(1-2), 3-17.

Mariani, M. M., Di Felice, M., & Mura, M. (2016). Facebook as a destination marketing tool: Evidence from Italian regional Destination Management Organizations. *Tourism Management*, 54, 321-343.

Marine-Roig, E., & Clavé, S. A. (2015). Tourism analytics with massive user-generated content: A case study of Barcelona. *Journal of Destination Marketing & Management*, 4(3), 162-172.

Matthes, J., & Kohring, M. (2008). The content analysis of media frames: Toward improving reliability and validity. *Journal of Communication*, 58(2), 258-279.

McCartney, G. (2008). Does one culture all think the same? An investigation of destination image perceptions from several origins. *Tourism Review*, *63*(4), 13-26.

Mensah, Y., & Chen, H. Y. (2013). Global clustering of countries by culture–an extension of the GLOBE study. Rutgers University Center for Governmental Accounting Education and Research (CGAER). Available at: http://ssrn.com/abstract=2189904.

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.

Moro, S. (2020). Guest satisfaction in East and West: evidence from online reviews of the influence of cultural origin in two major gambling cities, Las Vegas and Macau. *Tourism Recreation Research*, DOI: 10.1080/02508281.2020.1759002.

Moro, S., Lopes, R. J., Esmerado, J., & Botelho, M. (2020). Service quality in airport hotel chains through the lens of online reviewers. *Journal of Retailing and Consumer Services*, 56, 102193.

Moro, S., Rita, P., & Coelho, J. (2017). Stripping customers' feedback on hotels through data mining: The case of Las Vegas Strip. *Tourism Management Perspectives*, 23, 41-52.

Moro, S., Rita, P., & Oliveira, C. (2018). Factors influencing hotels' online prices. *Journal of Hospitality Marketing & Management*, 27(4), 443-464.

Oh, H. (1999). Service quality, customer satisfaction, and customer value: A holistic perspective. *International Journal of Hospitality Management*, 18(1), 67-82.

Park, S. B., Ok, C. M., & Chae, B. K. (2016). Using twitter data for cruise tourism marketing and research. *Journal of Travel & Tourism Marketing*, 33(6), 885-898.

Prayag, G., & Ryan, C. (2011). The relationship between the ‘push’and ‘pull’factors of a tourist destination: The role of nationality–an analytical qualitative research approach. Current Issues in Tourism, 14(2), 121-143.

Raguseo, E., Neirotti, P., & Paolucci, E. (2017). How small hotels can drive value their way in infomediation. The case of ‘Italian hotels vs. OTAs and TripAdvisor’. *Information & Management*, 54(6), 745-756.

Rita, P., Brochado, A., & Dimova, L. (2018). Millennials’ Travel Motivations and Desired Activities Within Destinations: A Comparative Study of the US and the UK, *Current Issues in Tourism*, DOI: 10.1080/13683500.2018.1439902.

Ritchie, J. B., & Zins, M. (1978). Culture as determinant of the attractiveness of a tourism region. *Annals of Tourism Research*, 5(2), 252-267.

Rose, M., & Blodgett, J. G. (2016). Should hotels respond to negative online reviews?. *Cornell Hospitality Quarterly*, 57(4), 396-410.

Salifou, C. K., & Haq, I. U. (2017). Tourism, globalization and economic growth: a panel cointegration analysis for selected West African States. *Current Issues in Tourism*, 20(6), 664-667.

Statista (2018) www.statista.com

Tolkach, D., & Pratt, S. (2019). Globalisation and cultural change in Pacific island countries: the role of tourism. *Tourism Geographies*, DOI: 10.1080/14616688.2019.1625071.

Tourism Economics (2017) *The Economic Impact of Tourism in New York*. Tourism Economics Company. Philadelphia, USA.

van der Hoeven, A. (2019). Historic urban landscapes on social media: The contributions of online narrative practices to urban heritage conservation. *City, Culture and Society*, DOI: 10.1016/j.ccs.2018.12.001.

Waldinger, R. (1992). Taking Care of the Guests: The Impact of Immigrants on Services-An Industry Case Study. *International Journal of Urban and Regional Research*, 16(1), 97-113.

Wei, T., Lu, Y., Chang, H., Zhou, Q., & Bao, X. (2015). A semantic approach for text clustering using WordNet and lexical chains. *Expert Systems with Applications*, 42(4), 2264-2275.

Wood, S. A., Guerry, A. D., Silver, J. M., & Lacayo, M. (2013). Using social media to quantify nature-based tourism and recreation. *Scientific Reports*, 3, 2976, 1-7.

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.

Ye, Q., Li, H., Wang, Z., & Law, R. (2014). The influence of hotel price on perceived service quality and value in e-tourism: An empirical investigation based on online traveler reviews. *Journal of Hospitality & Tourism Research*, 38(1), 23-39.

Zhou, X., Wu, B., Jin, Q., Li, W., & Yen, N. Y. (2016). Personal data analytics to facilitate cyber individual modeling. In *Dependable, Autonomic and Secure Computing, 14th Intl Conf on Pervasive Intelligence and Computing*, 2nd Intl Conf on Big Data Intelligence and Computing and Cyber Science and Technology Congress (DASC/PiCom/DataCom/CyberSciTech), 2016 IEEE 14th Intl C (pp. 39-46). IEEE.

Table 1 - Studies on NYC based on social media.

Study	**Goal**	**Source**	**Method**
Kim et al. (2016)	Identify and compare satisfiers (reviews rated 4 or 5) and dissatisfiers (reviews rated 1 or 2)	919 reviews from 100 hotels extracted from TripAdvisor	Manual content analysis approach
Rose & Blodgett (2016)	Find the benefits of answering online negative reviews about hotels and restaurants	255 respondents	Survey
Lee et al. (2017)	Explore the relation between sentiments expressed in online reviews and review helpfulness	69,202 reviews from 488 hotels extracted from TripAdvisor	Sentiment analysis for obtaining review valence and emotional intensity. Binomial regression to analyze the dependent variable, the number of helpful votes
Xiang et al. (2017)	Examine information quality in 3 major online platforms, TripAdvisor, Expedia and Yelp (NYC was used as the test case)	438,826 reviews from TripAdvisor, 351,182 from Expedia, and 30,770 from Yelp	Topic modeling, sentiment analysis, and a Naïve Bayes classifier to model sentiment polarity. Linear regression between score and review characteristics, and between helpfulness and review characteristics
Ahn et al. (2017)	Analyze tourist satisfaction depending on the traveling group	125,076 reviews of 322 hotels collected from Booking.com	Regression analysis (ordinary least squares) to examine whether a statistically significant difference exists in ratings between groups

Table 2 - Studies applying Big Data Analytics to social media data.

Study	Goal	Source	Method	Region
Wood et al. (2013)	Test if geotagged photos can be used to approximate visitation rates	Geolocations of 197M geotagged photographs uploaded to Flickr from 2005-2012.	Analysis of covariance (ANCOVA); R statistical software (maps package)	836 world recreational sites
Marine-Roig & Clavé (2015)	Highlight the usefulness of big data analytics to support smart destinations	+100k reviews from travel blogs and online travel reviews	Web structure mining to collect data; web content mining for content analysis	Barcelona, Spain
Mariani et al. (2016)	Explores how Italian regional Destination Management Organizations (DMOs) use Facebook to promote their destinations	33,597 Facebook posts and comments published on Italian DMOs during 2013	Facebook Graph API to collect data; Python script to compute engagement metrics	Italy
Park et al. (2016)	Discuss and demonstrate social media analytics in cruise travel	50,414 tweets from Twitter between May 2 and June 5, 2014	ScraperWiki for collecting data; NLP; descriptive analysis (RapidMiner); SNA (Gephi)	NA
Edwards et al. (2017)	Understand the knowledge-sharing and co-production of trip-related online knowledge	115,847 threads with 8,346 conversations between 2010 and 2014 from TripAdvisor	Python script to extract data; Gephi and Leximancer for visualization and SNA; SPSS for statistical analysis	New South Wales, Australia
Liu et al. (2017)	Examine the behaviors of Chinese tourists in Switzerland	103,778 Weibo (Twitter-like SN) messages about Swiss locations from 2013 to 2015	Semantic-based linked data methodology; Babelfy for disambiguation and entity linking; GraphDB for data manipulation; DBpedia to identify a total of 16,677 concepts	Switzerland
Miah et al. (2017)	Analyze social media data to support strategic decision-making in destination management organizations	238,290 photos from 7,392 tourist's Flickr accounts published between 2011 and 2015	Clustering technique (P-DBSCAN) to identify popular areas of interest (Matlab)	Melbourne, Australia
Del Vecchio et al. (2017)	Value creation process for a Smart Tourism Destination based on Social Big Data	767 posts, 302 users, 2M reach, 6M impressions, from April 2015 to May 2016 in Facebook, Twitter and Instagram	Keyhole for cluster analysis, and Buzztrack sentiment analysis and social media monitoring	Apulia, Italy
Raguseo et al. (2017)	Evaluate how small hotels can drive value their way in infomediation	62,865 travelers' reviews on TripAdvisor	11 fixed effects regression model	Italy

Table 3 - NYC hotels in Booking.com.

Stars	Nr. of hotels	Nr. of reviews	Average Booking.com score
1 or 2	20	5,173	7.09
3	91	36,004	8.15
4	153	62,930	8.33
5	43	11,190	8.61
Total	**307**	**115,297**	

Table 4 - Cultural clusters aggregating countries.

Cultural cluster	Countries
African	Angola, Kenya, Nigeria, South Africa, Tanzania, ...
Anglo-Saxon	Australia, Canada, Ireland, United Kingdom, ...
Confucian	China, Japan, Mongolia, Singapore, South Korea, ...
Eastern European	Bulgaria, Croatia, Hungary, Poland, Russia, ...
German	Austria, Germany, Luxembourg, Netherlands, ...
Latin-American	Argentina, Brazil, Colombia, Mexico, Venezuela, ...
Latin-European	France, Italy, Portugal, Spain, ...
Middle Eastern	Egypt, Jordan, Libya, Saudi Arabia, Turkey, ...
Nordic	Denmark, Finland, Iceland, Norway, Sweden, ...
South-East Asian	India, Indonesia, Malaysia, Philippines, Thailand, ...

Source: Mensah and Chen (2013).

Table 5 - Nr. reviews distribution per cultural cluster and hotel star category.

Culture \ Stars	1 or 2	3	4	5
African	147	1008	1544	310
Anglo-Saxon	2524	18142	34596	5845
Confucian	195	1435	2303	515
Eastern European	402	2183	2769	443
German	408	2598	4390	683
Latin-American	363	2509	3575	677
Latin-European	447	3113	4864	718
Middle Eastern	210	2161	4714	1301
Nordic	230	1218	1941	233
South-East Asian	247	1637	2234	465

Table 6 - Frequency for each category.

Category \ Classified	Total	(in %)	Negative	(in %)	Positive	(in %)
cleanliness	25,507	22.1%	7,130	6.2%	18,377	15.9%
food	37,037	32.1%	17,933	15.6%	19,104	16.6%
location	64,595	56.0%	4,303	3.7%	60,292	52.3%
price	19,817	17.2%	13,762	11.9%	6,055	5.3%
staff	45,388	39.4%	10,743	9.3%	34,645	30.0%

Table 7 - Analyzed categories.

Category	**Lexicon**
Cleanliness	washed, dirty, spotless, ...
Food	restaurant, taste, flavors, wine, cuisine, meal, ...
Location	place, sight, scenery, ...
Price	money, expensive, cost, dollar, ...
Staff	employees, workers, waitress, ...

Source: Calheiros et al. (2017); Prayag and Ryan (2011).

Table 8 - GNI per capita, Atlas method.

Culture	**GNI per capita**
African	4%
South-East Asian	6%
Middle Eastern	7%
Eastern European	9%
Latin-European	9%
Confucian	10%
Anglo-Saxon	12%
Latin-American	12%
Nordic	15%
German	15%

Source: World Bank Group (https://data.worldbank.org/), World Development Indicators, 01/March/2018.

Table 9 - 2018 KOF Globalization Index: Social Dimension Social Globalization Index.

Culture	**Social Globalization Index (Average)**
Latin-American	123.8
South-East Asian	119.8
African	107.8
Middle Eastern	100.5
Confucian	95.2
Latin-European	95.0
German	89.5
Nordic	77.7
Eastern European	74.5
Anglo-Saxon	45.1

Source: https://www.kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html (also adopted by Salifou & Haq, 2017).

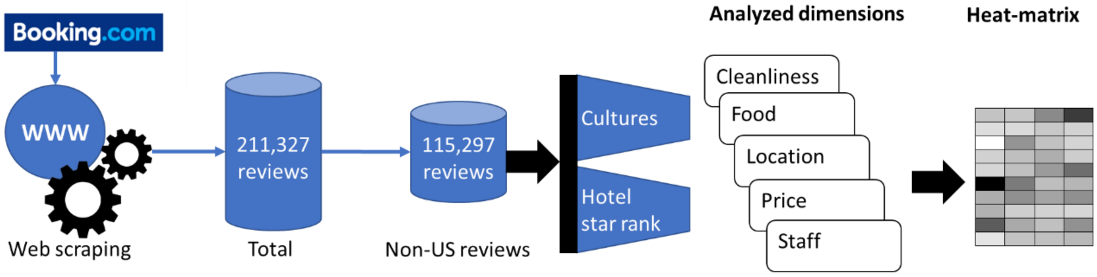

Figure 1 - Undertaken procedure.

Cleanliness

Stars / Culture	1 or 2	3	4	5	$\overline{x}$	σ
African					0.113	8.2%
Anglo-Saxon					0.199	8.2%
Confucian					0.161	5.6%
Eastern European					0.157	9.2%
German					0.134	10.2%
Latin-American					0.084	11.7%
Latin-European					0.142	8.5%
Middle Eastern					0.100	7.6%
Nordic					0.178	10.0%
South-East Asian					0.144	9.4%
$\overline{x}$	0.047	0.264	0.169	0.084		
σ	5.6%	3.1%	4.3%	5.4%		

Food

Stars / Culture	1 or 2	3	4	5	$\overline{x}$	σ
African					-0.076	5.7%
Anglo-Saxon					0.033	3.5%
Confucian					0.037	3.2%
Eastern European					-0.015	3.0%
German					0.033	7.3%
Latin-American					0.023	6.3%
Latin-European					0.006	2.9%
Middle Eastern					-0.059	5.9%
Nordic					0.045	2.2%
South-East Asian					-0.041	7.1%
$\overline{x}$	0.018	0.018	-0.021	-0.021		
σ	9.6%	3.6%	4.9%	5.3%		

Location

Stars / Culture	1 or 2	3	4	5	$\overline{x}$	σ
African					0.369	1.2%
Anglo-Saxon					0.392	0.3%
Confucian					0.416	0.8%
Eastern European					0.396	2.1%
German					0.391	2.0%
Latin-American					0.395	0.4%
Latin-European					0.390	1.1%
Middle Eastern					0.397	0.6%
Nordic					0.400	1.2%
South-East Asian					0.411	2.7%
$\overline{x}$	0.397	0.399	0.397	0.390		
σ	2.1%	1.6%	0.7%	2.5%		

Price

Stars / Culture	1 or 2	3	4	5	$\overline{x}$	σ
African					-0.238	11.3%
Anglo-Saxon					-0.141	15.4%
Confucian					-0.159	14.2%
Eastern European					-0.131	11.2%
German					-0.175	14.8%
Latin-American					-0.149	13.5%
Latin-European					-0.180	12.3%
Middle Eastern					-0.219	12.8%
Nordic					-0.113	15.2%
South-East Asian					-0.193	8.8%
$\overline{x}$	-0.022	-0.075	-0.242	-0.340		
σ	6.9%	4.2%	3.4%	4.1%		

Staff

Stars / Culture	1 or 2	3	4	5	$\overline{x}$	σ
African					0.213	3.4%
Anglo-Saxon					0.259	3.4%
Confucian					0.147	6.4%
Eastern European					0.228	6.0%
German					0.249	1.4%
Latin-American					0.237	4.9%
Latin-European					0.220	3.6%
Middle Eastern					0.162	5.3%
Nordic					0.264	1.4%
South-East Asian					0.125	6.4%
$\overline{x}$	0.235	0.249	0.209	0.149		
σ	5.1%	2.9%	5.3%	7.0%		

Figure 2 - Average positive/negative score per cultural cluster and hotel star category.

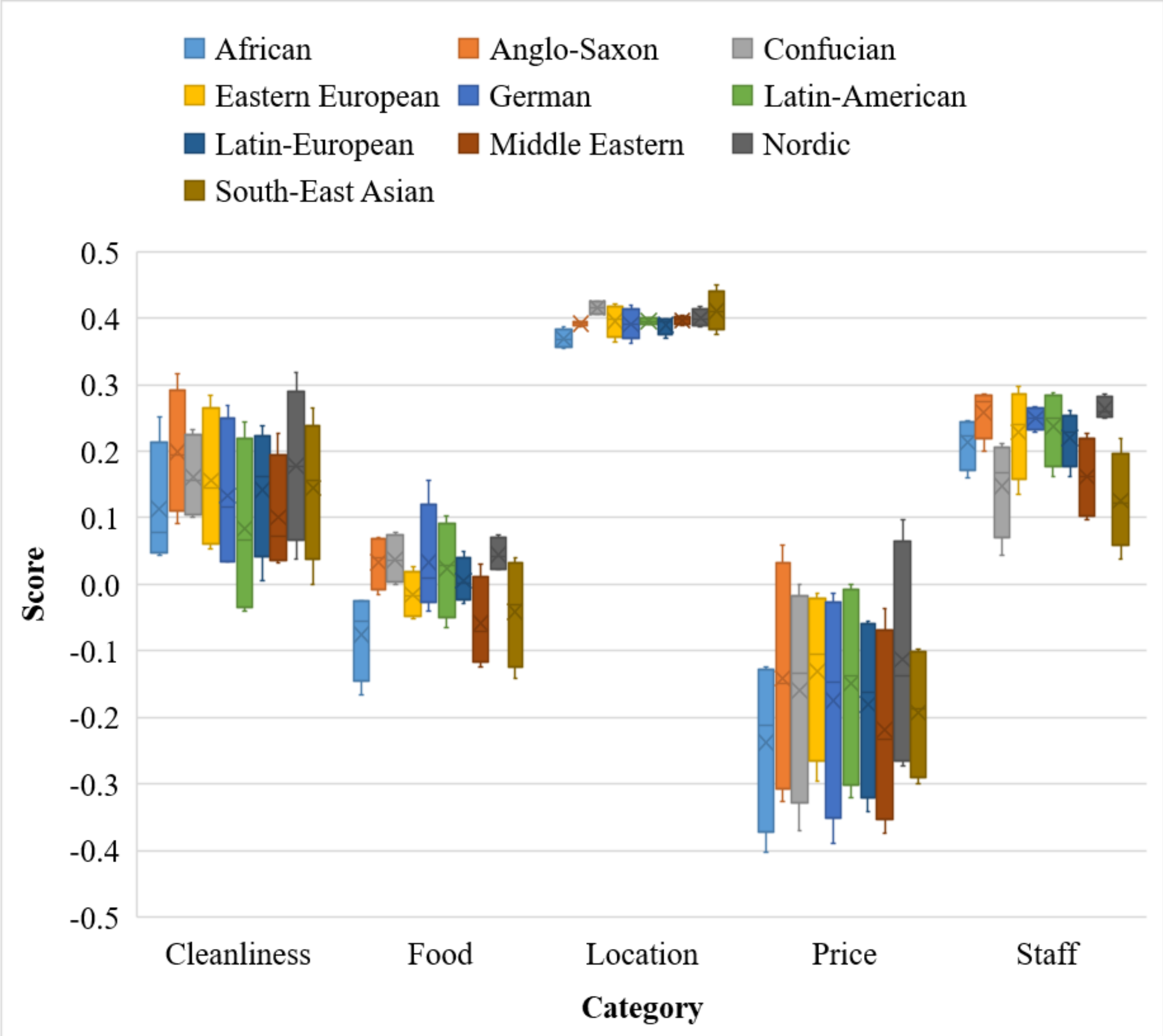

Figure 3 - Boxplots for the categories per culture.