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A sentiment analysis on Lisbon hotels

David Gonçalo de Araújo Rodrigues

Dissertation presented as the partial requirement for obtaining a Master's degree in Information Management

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HOTEL ONLINE REVIEWS: WHAT INFLUENCES THE SENTIMENT AND RATING?
A SENTIMENT ANALYSIS ON LISBON HOTELS

by

David Gonçalo de Araújo Rodrigues

Dissertation presented as partial requirement for obtaining the Master's degree in Information Management, with a specialization in Information Systems and Technologies Management

Advisor: Paulo Miguel Rasquinho Ferreira Rita, PhD

Co Advisor: Ricardo Filipe Ramos, PhD

August 2020

ACKNOWLEDGEMENTS

This dissertation is an important milestone in my academic, professional, and personal life. It was a long and complex work and it is more than fair to thank my family and friends for all the support along this path.

In particular, I want to show the deepest gratitude to my friend Pedro Guerra. To my outstanding girlfriend Ana Paes de Faria, who stood with me every step of the process, supporting me, and showing total availability every single day, an incalculable thank you.

Finally, I want also to leave a word of appreciation to Professor Paulo Rita and Professor Ricardo Filipe Ramos who helped me improve my work with their useful guidance and professionalism.

ABSTRACT

This study analyzes 38,292 reviews from 192 Lisbon Hotels posted in Booking.com and TripAdvisor for hotels located in Lisbon, Portugal. The aim of this research is to understand if the hotel categories and nationality of the reviewer influence the sentiment and the ratings of the reviews. Moreover, it also evaluates whether the review ratings in Booking.com are inflated in comparison with TripAdvisor. A sentiment analysis on all the reviews was performed using Semantria, a software from Lexalytics.

The key insights of this research are that the hotel category influences the sentiment on the review, even though the sentiment does not increase as the hotel category increases. Furthermore, this study also found statistically significant differences between the sentiment depending on the nationality of the reviewer. This work also rejects the hypothesis that the review ratings on Booking.com are inflated in comparison with TripAdvisor.

Finally, this study provides insights to hotel managers who should focus on meeting the customers' expectations and adapt the service provided according to the nationality of the reviewer. Moreover, by not providing evidence that Booking.com review ratings are inflated, this study restores the confidence of the stakeholders in the reliability of the scoring system applied by that platform.

KEYWORDS

sentiment analysis; online reviews; nationality; hotels located in Lisbon; tourism

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LIST OF ABBREVIATIONS AND ACRONYMS

COP	Consumer Opinion Platform
eWOM	Electronic Word of Mouth
GDP	Gross Domestic Product
HOTREC	Umbrella Association of Hotels, Restaurants, Bars and Cafes and similar establishments in Europe
ICT	Information and Communication Technologies
NLP	Natural Language Processing
OECD	Organisation for Economic Co-operation and Development
OM	Opinion Mining
OTA	Online Travel Agency
RNT	Registo Nacional de Turismo
SA	Sentiment Analysis
UNWTO	United Nations World Tourism Organization
WTTC	World Travel & Tourism Council

1. INTRODUCTION

In the latest centuries, the phenomenon of globalization spread across the earth, connecting and integration hundreds of countries worldwide into a single global economy. Therefore, and, with globalization being considered a key driver for economic growth, it is possible to conclude that it is, also, a driver for accessing new markets and services at international level, which is particularly important for the tourism sector (Balsalobre-Lorente et al, 2020). The development of transportation and the emergence of Information and Communication Technologies (ICT) boosted the process and allowed an easier circulation of capitals, people, goods, and services. The desire to explore new places and discover new cultures led tourism to greatness, becoming one of the key sectors in the global economy (Kontogianni & Alepis, 2020). In fact, from 1950 to 2018, the number of international tourist arrivals grew from 25 million to 1400 million (Our World in Data, 2020) and is expected to reach 1800 million by 2030 (UNWTO, 2017), being responsible by 420 million jobs by 2029 (WTTC, 2019). The tourism sector is, nowadays, for developing countries, an important method to ensure economic growth while continuously increasing the relevance of the sector itself (Lee & Chang, 2008).

The relevance of tourism for today's economy is undeniable and the forecasts only seem to anticipate a lasting importance for the coming decades. Nevertheless, there is also a need to look at tourism history to understand important events such as the *Grand Tour* (Towner, 1985), the influence of Industrial Revolution and the development of transportation (Daniel, 2010; Holden, 2016) and the appearance of tourism of masses (Holden, 2016). Each of these milestones significantly impacted the tourism sector and, to some extent, society itself, promoting important socio-cultural, political, and economic changes (Holden, 2016).

In Portugal, the tourism sector can be considered the "engine" of the economy and, in 2019, contributed with 16.5% for the country's GDP and was responsible for more than 900 thousand jobs (WTTC, 2020). However, this was not always the case. In fact, Portugal's role in the tourism history is somewhat curious. The country started to promote the development of the sector with some delay in comparison to other European countries but is one of the founders of the current World Tourism Organization (Cunha, 2010). The country relies on the so-called "sun, sea and sand" product to promote its tourism, which exerts pressure in some regions of the country. It urges the need to develop alternative solutions to diminish this pressure and solve the issue of seasonality (Cravidão & Cunha, 1993; Daniel, 2010).

Hotels are important assets in the tourism sector and the relationship between the performance of the tourism sector and hotels is close, being that the first influences the later both directly and indirectly (Chen, 2010; Mucharreira et al., 2019).

Tourism, particularly hotel industry, is characterized by information asymmetry, a problem introduced by Akerlof (1970) in which the seller has more information about a product or service than the buyer. This situation is exacerbated in services since there is nothing the buyer can see, feel, smell, taste or hear before consuming the service itself (Núñez-Serrano et al., 2014; Martin-Fuentes, 2016). Since hotels are one of the key service providers in the tourism sector, there is a need to develop a standard to assure some trust and transparency to the consumers and, across the globe, it is universally accepted the hotel star-rating system. Portugal complies with the hotel star-rating system and *Turismo de Portugal* is responsible for granting each star to hotels in the country, provided that they meet the mandatory requirements fixed by the legislation (Mohsin et al., 2019; Turismo de Portugal, 2020a).

The above-mentioned growth in ICT also impacted tourism through the development of social media, blogs and online platforms in which consumers share their experience with other consumers or/and potential consumers. This new reality impacts the way hotels manage their communication in an online environment and revolutionized the way consumers plan and book their trips, being that 90% of the consumers claim that they read this electronic word-of-mouth before performing the final decision (Akhtar et al., 2019).

Since the opinions shared by consumers on online platforms correspond to their narrative around the experience provided by the hotel and their perception of the quality of the service and they are usually not biased. This information is perceived as trustworthy by other consumers and can be seen as a mean to align expectations before booking their reservation. Therefore, it seems important to consider online reviews an important tool to measure service quality nowadays. Several studies were published in the field and multiple models developed to measure service quality. However, every model has its own contributions and limitations.

Despite the guidance given by the hotel star-rating system, recent studies start to question its reliability as the criteria tend to follow infrastructural needs of the building rather than the actual needs of the consumers, while others posit the growing relevance of online reviews and electronic word-of-mouth (eWOM).

In this sense, the present study intends to contribute to the existing literature by performing a sentiment analysis on 38,292 online reviews of 192 Lisbon hotels and measuring how hotel categories, the nationality of the reviewer and the platform where the review was submitted influences the sentiment on service quality. Choosing to implement a *sentiment analysis* allows this research to capture the sentiment around certain features of the service provided, something that cannot be achieved when considering only quantitative metrics (e.g. rating). Finally, the study provides useful inputs to help hotel managers to understand if they are meeting their target audience expectations.

The remaining of the study is structured as follows:

- Chapter 2 includes a literature review on the relevance of tourism for the economy and its history, detailing the Portuguese case. Later, it will explore the hotel industry and the hotel star-classification system, providing an overview on the impacts of the technological progress in the tourism sector and the emergence of online reviews and eWOM. The chapter ends with a summary table of the existent literature, highlighting the main contributions and limitations of the previous studies.
- Chapter 3 includes the methodological framework around sentiment analysis and highlights the main advantages and disadvantages of the methodology, before defining the research hypotheses and the sample of the study.
- Chapter 4 includes the analysis and discussion of the results obtained and the theoretical and practical implications derived from the results.
- Chapter 5 includes the conclusions of the study.

- Finally, Chapter 6 includes the limitations of the study and future work opportunities.

2. LITERATURE REVIEW

The Tourism sector is becoming increasingly important for the global economy. It also plays an important role in the economic development of countries that benefit from its exploitation. Tourism has a long story among mankind once it is deeply connected with the evolution of the world either in the social-cultural area or the political and economic fields. One of the tourism industry components relies on the accommodation sector, namely hotels, which has shown a similar behavior, with an exponential growth in the past years. Although, in this area there is an issue that concerns the customers and their service experience on hotels: information asymmetry. In order to surpass this problem, clients often rely on past experiences shared by other costumers about a service, product or company, which is called word-of-mouth. Nowadays with the new information and communication technologies word-of-mouth gained new ways of spreading data evolving into electronic word-of-mouth, which is accessible to everyone in technological platforms or websites. Following this introduction, the present chapter will approach in detail the tourism sector and the hotel stars classification system, before considering the impact of online reviews and eWOM.

2.1. TOURISM SECTOR

2.1.1. Definition of Tourism

The UNWTO (2010) defines tourism as "a social, cultural and economic phenomenon related to the movement of people to places outside their usual place of residence, pleasure being the usual motivation.". Albeit there is still no consensus into a single definition of tourism, several countries use the one proposed by UNWTO (Netto, 2009).

2.1.2. Tourism relevance for the global economy

The importance of tourism for the global economy is undeniable as the sector is growing at a rapid pace on a global scale, claiming its spot as one of the main sectors in the economy (Kontogianni & Alepis, 2020). In both developing and developed countries, governments see tourism as a path to development and economic growth, promoting several initiatives to support the sector with the objective of creating more jobs and generating more income (Ivanov & Webster, 2007; Lee & Chang, 2008; Shafiee et al., 2019). One research compared the economic impacts of tourism development in Organization for Economic Co-operation and Development (OECD) countries versus 32 non-OECD countries, concluding that the impact is higher for non-OECD countries. Moreover, the authors discovered that "unidirectional causality relationships exist from tourism growth to economic development in OECD countries, but bidirectional causality relationships are found between the two variables in non-OECD countries" (Lee & Chang, 2008). This means that, in OECD countries, tourism growth boosts economic development but there is no relationship on the opposite direction. Regarding non-OECD countries, the relationship is observed in both directions – tourism growth boosts economic development and economic development is also a way to boost tourism growth (Lee & Chang, 2008).

From 1950 to 2018, the number of international tourism arrivals increased more than 5500% to reach a record of over 1400 million people. In 2019 alone, the travel & tourism sector grew more than 3.5%, contributing with 10.3% to the global GDP and supporting 330 million jobs worldwide (WTTC, 2020) following 10 years of significant development with the number of international tourism arrivals raising from 897 million in 2009 to 1409 million people in 2018 (UNWTO, 2020b) (*Figure 1*).

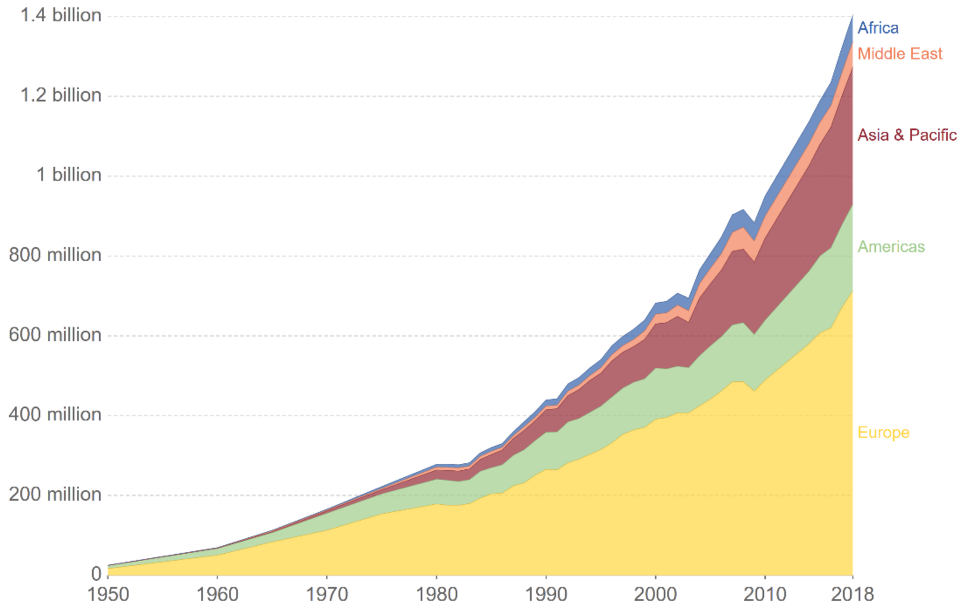

Figure 1. Evolution of international tourist arrivals per region from 1950 to 2018
Source: Adapted from Roser (2017)

In 2018, 8 out of the 10 top destinations regarding international tourist arrivals were also part of the destinations that collected more revenue from tourism – France, Spain, United States of America, China, Italy, Germany, Thailand, and United Kingdom. Moreover, the top 10 on the left account for 40% of the total international tourist arrivals worldwide, while the top 10 on the right account for 50% of the total receipts worldwide. Although Luxembourg isn't in *Figure 2*, it is the country that has the higher receipt per arrival – USD 4900 per tourist (UNWTO, 2019).

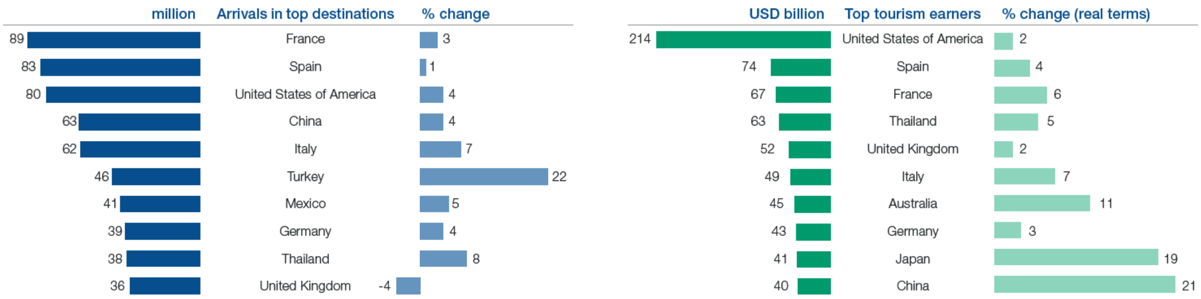

Figure 2. Top destinations in terms of arrivals and earnings
Source: UNWTO (2019)

The forecasts for 2030 claim that the number of international tourist arrivals will reach 1800 million tourists, an average increase of 43 million people per year. (UNWTO, 2017; Kontogianni & Alepis, 2020). This significant growth in tourism is expected to impact two important variables: the total contribution to the global GDP by reaching 11,5% and the number of jobs supported by the travel & tourism sector with forecasts achieving 420 million by 2029 (WTTC, 2019a) (*Figure 3*).

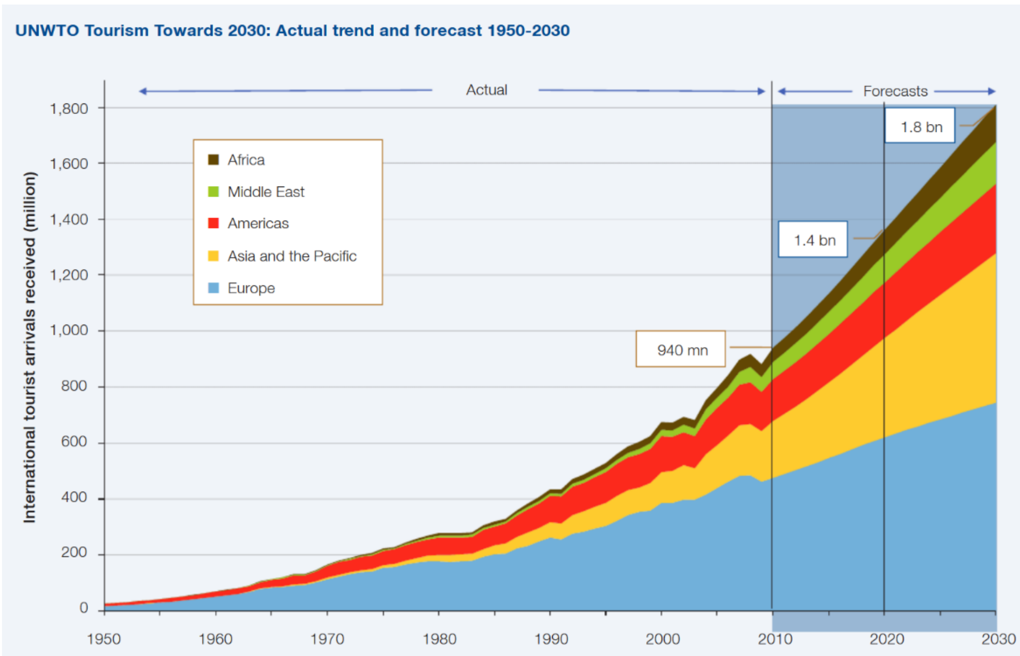

Figure 3 - Actual Trend and forecast 1950-2030 for World Tourism
Source: UNWTO (2017)

2.1.3. Historical background

Tourism history blends itself with the history of civilizations and the evidence from tourism activity reports back to the ancient Greece and Roman empire (Towner, 1995; Costa, 2005). In fact, the motivations and physiological needs that the romans sought to satisfy are not so different from those from modern societies (Holden, 2016). Society evolved from these ancient times and some of the socio-cultural, political and economic changes significantly contributed to tourism development (e.g. Industrial Revolution).

The contemporaneous history of tourism starts with the emergence of the *Grand Tour*, where wealthy young men, being the English the pioneers, travelled in Europe to conclude their educations and grant a place in the Royal Court. The origins of the movement remain unclear varying from the sixteenth century to the early eighteenth century and its demise is attributed to the French Revolutionary wars in the end of the eighteenth century, the appearance of the railways in the decade of 1840 or the growth in the number of middle class tourists. Towner (1985) considers the *Grand Tour* to be an important milestone in tourism history alongside with the central role of Britain and Western Europe in its genesis, yet the same author argues that tourism literature is still missing a more comprehensive work regarding eastern countries (Towner, 1995).

The *Grand Tour* is also often associated with the origin of the word "tourist", derived from the French *touriste*, and used to designate those who participated in it and popularized by Stendhal' in his book *Mémoires d'un touriste* from 1838 (Leiper, 1979; Towner, 1985; Costa, 2005; McCabe, 2009; Cunha, 2010; Holden, 2016). Nevertheless, only a century later, in 1937, the League of Nations proposed the first definition of international tourist – someone who "visits a country other than that in which he habitually lives for a period of at least twenty-four hours" (Leiper, 1979:393). In 1968, a new definition was approved by the International Union of Official Travel Organizations (now the UNWTO) – "temporary visitors staying at least twenty-four hours in the country visited and the purpose of whose journey can be classified under one of the following headings: (a) leisure (recreation, holiday, health, study, religion, and sport), (b) business, family, mission, meeting." - and countries were encouraged to use it (Leiper, 1979:393).

The Industrial Revolution and the emergence of legislation to grant the right to leisure and holidays (e.g. Bank holiday Acts in 1871 and 1875) introduced new socio-economic impacts during the nineteenth century and paved the way to a clearer distinction between work and personal life. Alongside this, the technological progress in transportation through the development of railways and steamships, led to the shrinkage of the barriers to mobility and allowed different countries to easily connect (Daniel, 2010; Cunha, 2010; Holden, 2016). Thomas Cook took advantage of this technological progress and created the first touristic package that consisted on a tour by train for 570 people between Leicester and Loughborough, in 1841, that is considered to be another important milestone in the history of tourism (Costa, 2005; Holden, 2016).

The last important milestone regarding tourism is known as mass tourism. It started in the late nineteenth century in domestic tourism due to the movement of people from rural areas towards big cities and expanded to the international panorama in the twentieth century. Supported by more income, lower travel costs and commercial aviation, international mass tourism became a reality, particularly in Europe due to its close geography, in the 50s, and boomed in the 60s and 70s leading to the growing popularity of the Mediterranean and the Caribbean due to its warm weather (Costa, 2005; Holden, 2016).

2.1.3.1. The Portuguese case

Tourism in Portugal reports back to the beginning of the thirteenth century where the king decreed that the people should host and feed for free the king and his court, the high lords, the army and other travelers. Nevertheless, following these remote times, only in the twentieth century, tourism started to be envisioned as an opportunity for the country (Costa, 2005).

After a significant public investment in the 1860s, the country landed in a financial recession, in the turn of the century, caused by the high level of sovereign debt. Albeit starting behind regarding other European countries, Portugal created, in the beginning of the twentieth century, *Sociedade Propaganda de Portugal* with the objective of promoting the country to foreign visitors. One of its most important initiatives was the establishment of railway and maritime connections with Europe and America, respectively (Cunha, 2010).

Despite its delay in recognizing tourism as an economic opportunity for the country, Portugal's role in international tourism was remarkable and the country remains as one of the founders of the World Tourism Organization (Cunha, 2010).

Portugal unravels to the world in the 50s and starts to position itself as an important country in respect to the tourism of "sun, sea and sand" due to its pleasant weather and coast. The 60s accelerated the process and, between 1960 and 1973, tourism highly contributed to an increase in the Portuguese GDP and to the transfer of human capital from the primary sector to the tertiary sector (Cravidão & Cunha, 1993; Vieira, 2007).

In the second half of the twentieth century, Portugal steadily increased the number of international tourist arrivals, apart from the mid-70s, 1992-1993 and 2002-2003. In the mid-70s, the reasons for the impairment in the number of tourist arrivals are due to the 1973 oil crisis and the political instability lived in the country, that culminated in a revolution on April 25th, 1974. In 1992-1993, the small decrease is due to a rise in competition for the same product ("sun, sea and sand"). Finally, in 2002-2003, the 9/11 and the entry into force of the euro significantly impacted tourism in Portugal (Milheiro & Santos, 2005; Vieira, 2007; Daniel, 2010). Despite this consistent increase, five countries – France, Germany, The Netherlands, Spain and United Kingdom - account for almost 80% of the number of tourists arriving to Portugal, which may denote a concentration problem, in case one of these economies faces a complex situation. (Vieira, 2007; Daniel, 2010) (*Figure 4*).

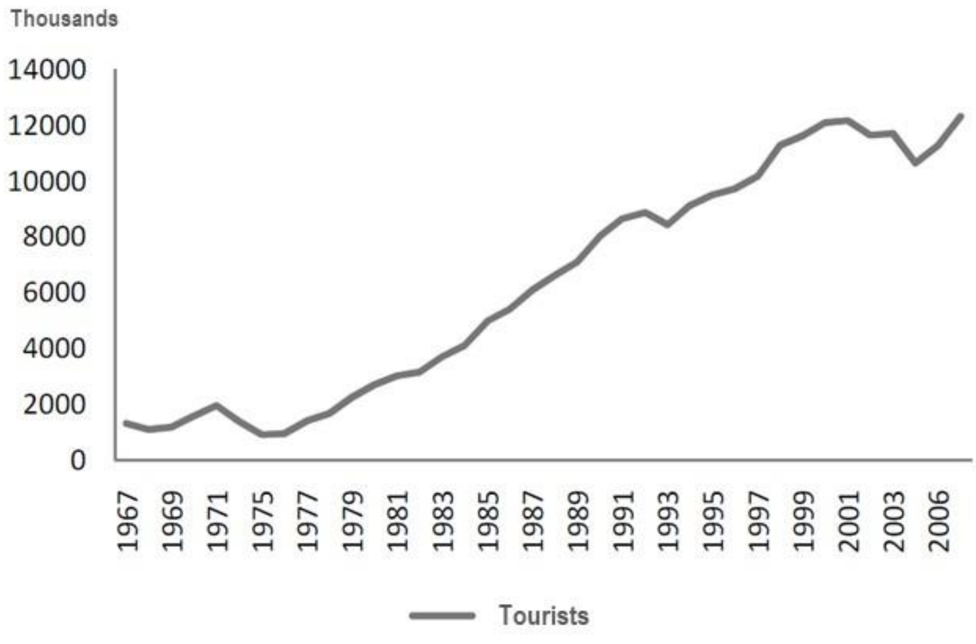

Figure 4 – Tourists entering Portugal (1967 – 2006)
Source: Adapted from Daniel (2010:257)

The abovementioned concentration problem is even more evident considering that, in 2008, France, Germany, The Netherlands, Spain and United Kingdom accounted for 65% of the total revenue generated by tourism in Portugal. Moreover, in 1970 these same countries already represented 44% of the total revenue (Daniel, 2010) (*Figure 5*).

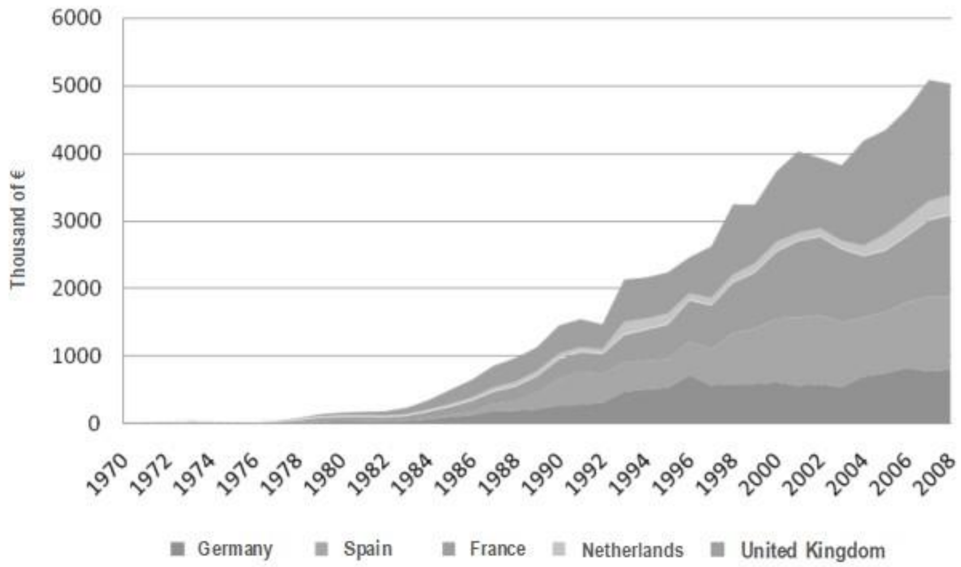

Figure 5 – Revenues from Tourism in Portugal per country of origin (1970 – 2008)
Source: Adapted from Daniel (2010:267)

The increase in demand forced Portugal to invest and modernize its infrastructures, increasing the number of hotels and available beds, particularly in Lisboa, Madeira and Algarve. In the 60s, Algarve was a somewhat irrelevant region of the country, however, it grew to be the main attraction in Portugal in the turn of the millennium, having the highest capacity to accommodate tourists (Vieira, 2007).

The above mentioned tourism product that dominates Portugal's offer exerts a significant pressure over a few regions of the country (e.g. Algarve), and there is a clear need to create new products to attract tourists, solve the problem of seasonality and satisfy the growing demand for rural tourism – an alternative to escape the overcrowded regions (Cravidão & Cunha, 1993; Daniel, 2010).

In the recent years, Portugal's tourism exploded to reach 22.8 million international tourist arrivals in 2018. Particularly, between 2015 and 2016 there is an increase of over 80% (UNWTO, 2020a). In 2019, the travel & tourism sector contributed with 16.5% to the country GDP and was responsible for more than 900 thousand jobs (WTTC, 2020) (*Figure 6*).

Figure 6 – Number of international tourist arrivals (% change) in Portugal from 2009 to 2018
Source: Adapted from UNWTO Tourism Data Dashboard Country Profile – Inbound Tourism (2020a)

2.1.4. Consumer satisfaction in the hotel industry

Consumer satisfaction is the result of a comparison between what was experienced and the initial expectations and is a key dimension to promote an increase in hotel demand (Xu & Li, 2016).

Zeithaml et al. (1985) combine four service features that distinguish them from products - intangibility, inseparability, heterogeneity and perishability – and summarize the key marketing problems that arise from those characteristics (*Table 1*). Intangibility means that, unlike products, one cannot rely on the human body senses to feel the service. Inseparability means that the production and consumption of the service happens simultaneously. Heterogeneity means that the service provided varies depending on the producer, consumer and even the day the service is provided. Perishability means that you cannot save a service. In the hotel industry, for example, one cannot save a room that has not been occupied for later, which enforces the importance of ensuring that offer meets demand at all times, something difficult to achieve in a seasonal industry (Zeithaml et al., 1985).

SERVICE FEATURES	RESULTING MARKETING PROBLEMS
Intangibility	1. Services cannot be stored. 2. Cannot protect services through patents. 3. Cannot readily display or communicate services. 4. Prices are difficult to set.
Inseparability	1. Consumer involved in production. 2. Other consumers involved in production. 3. Centralized mass production of services difficult
Heterogeneity	1. Standardization and quality control difficult to achieve.
Perishability	1. Services cannot be inventoried.

Table 1. Service features and resulting marketing problems
Source: Adapted from Zeithaml et al. (1985)

Consumer satisfaction and service quality are two concepts that, albeit distinct, are connected. The research from Zeithaml et al. (1985) contributed to the measurement of the quality of the service provided (Gu & Ryan, 2008). On the other side of the spectrum, Gu & Ryan (2008) argue that the cleanliness of the bedroom and the bathroom, the comfort of the bed, the quality of the food served and the overall performance of the staff are important vectors to promote consumer satisfaction. Ren et al. (2016) defined four dimensions that influence consumer satisfaction: tangible-sensorial experience, staff relational/interactional experience, aesthetic perception, and location. Their research asserts that consumers value a clean and quiet room, with comfortable showers. The room temperature must also be comfortable, and no odors must be smelled in the air (Ren et al., 2016). This research supports the relevance of cleanliness highlight in Gu & Ryan (2008) and indicates that the attitude of the staff is an important vector to promote consumer satisfaction (Ren et al., 2016).

Considering the above-mentioned benefits from ensuring customer satisfaction and promoting a high-quality service and the challenges that services pose when compared with products, it is of the utmost importance to consider the customers opinion when measuring the quality of that service. The hotel star-rating classification system, although considered an important metric to measure the quality of the hotel and as a first guidance for consumers (Huang et al., 2018; Mohsin et al., 2019), as proven to rely more on the technical aspects of the hotel than on the needs of the consumers (López Fernández & Serrano Bedia, 2004; Núñez-Serrano et al., 2014; Martin-Fuentes, 2016).

Over the years, millions of online reviews were analyzed and compared with the ratings attributed to hotels by third-party official entities, relying on different methodologies and models to measure the quality of the service provided. Nevertheless, no model is perfect and each one has its own limitations and contributions to the existing literature.

2.2. HOTEL STAR-RATING CLASSIFICATION SYSTEM

The tourism sector has a significant impact on the economy, being that its contraction/expansion accounts for an important part of the macroeconomic context. In this sense, the hotel industry is highly volatile to the cyclical behavior of the economy. Hence, following its relevance in the economy, the tourism sector indirectly impacts the hotel industry. Moreover, it also has a direct impact in the development of the hotel industry, influencing the occupancy rate and the revenues (Chen, 2010; Mucharreira et al., 2019).

The tourism activity is characterized by information asymmetry because the seller knows more about the product/service than the buyer, as the buyer will only know the real value of the product/service provided by the seller once it is consumed (Akerlof, 1970; Nicolau & Sellers, 2010; Núñez-Serrano et al., 2014; Martin-Fuentes, 2016). Around the global, the star-rating classification system is used to classify hotels, usually ranging from 1 to 5 stars. Yet, there is no common standard, which exacerbates the information asymmetry, since the criteria for attributing the number of stars might change from country to country and even from region to region – local regulation - as in the case of Spain. Moreover, these criteria tend to lean towards technical characteristics (infrastructures, size of the rooms, etc) of the hotel and not on the needs that consumers' want to fulfill (López Fernández & Serrano Bedia, 2004; Núñez-Serrano et al., 2014; Martin-Fuentes, 2016).

In Portugal, *Turismo de Portugal* is the official entity responsible for classifying each hotel based on a set of 197 requirements – being that 54 are mandatory for the hotel to receive 5 stars, 44 to receive 4 stars, 38 to receive 3 stars, 29 to receive 2 stars and 27 to receive 1 star[1] (Mohsin et al., 2019; Turismo de Portugal, 2020a). Since 2004, Europe is trying to bring harmonization to the equation by creating a single hotel classification system – Hotelstars Union - under the patronage of HOTREC, the umbrella Association of Hotels, Restaurants, Bars and Cafes. In 2020, 17 countries had already joined the initiative. Portugal, however, is not a member yet (Núñez-Serrano et al., 2014; Martin-Fuentes et al., 2018a; HOTREC, 2020).

Despite the abovementioned challenges, consumers still use the star-rating as a guidance when accessing the quality of a hotel and it is widely accepted that the higher the ranking, the better the quality of the hotel (Huang et al., 2018; Mohsin et al., 2019). Nonetheless, several studies assert that the star-rating system might be losing some credibility (López Fernández & Serrano Bedia, 2004; Núñez-Serrano et al., 2014), while others enforce the importance of online reviews

[1] Albeit the number of mandatory requirements, there are other requirements (e.g. those regarding the dimensions of the rooms) that need to be met.

during the consumer's decision process (Vermeulen & Seegers, 2009; Sparks & Browning, 2011; Akhtar et al., 2019) and as a means to reduce information asymmetry (Leung et al., 2013).

2.3. Online reviews, eWOM and the technological progress in tourism

The dynamism that characterizes the tourism sector forces firms to continuously innovate and adopt new technologies to develop a competitive advantage while improving their efficiency (Labanauskaitė et al., 2020). In this highly competitive sector, the objective on the supply side is to maximize profits by improving the customers' return rate. On the demand side, costumers create their own expectations regarding the service provided (Rhee & Yang, 2015). It is then crucial for hotels to understand what is most valued by the consumers, what influences their decision process and how to create a closer relationship (Tran et al., 2019).

The growth of the Internet allows information to be readily available to both parties and online platforms enables hotel managers to retrieve useful insights on the way consumers perceive the service provided, use the positive feedback to advertise their hotel and improve their service and reputation based on the negative reviews and comments. On the other hand, online platforms allow consumers to share their insights on their experience in the hotel and read the feedback from other users (Rhee & Yang, 2015). Therefore, this progress in ICT has carried substantial changes on the consumer's conduct (Sann et al., 2020; Egger et al., 2020).

Consumers have been sharing opinions about products or services and considerations about their sellers for decades (Torres et al., 2015). In fact, Westbrook (1987:261) defined word-of-mouth as "informal communications directed at other consumers about the ownership, usage, or characteristics of particular goods and services and/or their sellers". The progress in ICT led to the emergence of a new concept, the electronic word-of-mouth (eWOM), that uses the Internet-based technology to convey the information that previously was transmitted from mouth-to-mouth (Litvin et al., 2008).

Online platforms where consumers spread eWOM (Akhtar et al., 2019; Tran et al., 2019; Sann et al., 2020) and hotel websites (Tiago et al., 2020) are now a determinant factor to influence the consumers' purchase decision. More informed and demanding then ever (Daniel, 2010; Nicolau & Sellers, 2010), consumers rely on these alternative sources of information that are deemed to be accurate and trustworthy (Leung et al., 2013; Tran et al., 2019; Sann et al., 2020).

The impacts of the progress in ICT and the emergence of online reviews and eWOM in the tourism sector are significant. In fact, 90% of tourists read narratives shared by past consumers when planning their trips (Akhtar et al., 2019). Moreover, as the audience on these platforms grows, today's reviews will influence tomorrow's bookings, creating a domino effect (Veloso et al., 2019).

2.4. FUNDAMENTALS TO CONSIDER ONLINE REVIEWS AS A MEASURE OF HOTEL QUALITY

This study previously highlighted the correlation between the tourism sector and the hotel industry and how important was for the supply side (i.e. hotels) to increase the customers' return rate (Rhee & Yang, 2015). The hotel industry is a clear example where the customer acquisition cost is higher than the cost of retaining the current customers and where several initiatives must be developed to promote customer satisfaction and loyalty (Dominici & Guzzo, 2010).

Oliver (1980) asserts that satisfaction is a function of the expectations created by consumers prior to the purchase and the perceived disconfirmation of those expectations after the consumption of the product/ service, while Anderson & Sullivan (1993) posit that expectations do not influence satisfaction, as previously believed. Disconfirmation continues to play its role in the equation, but a new variable is proposed by the authors – service quality. The authors declare that service quality influences satisfaction and repurchase intentions. Moreover, failing to meet the consumers' expectations has a higher impact on customer satisfaction when compared with exceeding them, which clearly indicates the importance of continuously providing a high-quality service (Anderson & Sullivan, 1993).

Hotels face fierce competition nowadays and it is imperative to gain competitive advantage. Two key strategies to reach competitive advantage involve competing through price or quality. Whereas competing through low prices might hinder the ability of the hotels to ensure long term sustainability (Kandampully & Suhartanto, 2000) and can be easily copied by other players in the market (Lawton, 1999), providing a high quality service is a mean to stand apart from the competitors and to develop customer loyalty (Lawton, 1999; Kandampully & Suhartanto, 2000). Thus, service quality and customer satisfaction are the main goals of any service provider (Sureshchandar et al., 2002) and the foundations of customer loyalty (Sivadas & Baker-Prewitt, 2000; Saleem & Raja, 2014). In turn, loyal customers serve as brand ambassadors and spread positive word-of-mouth, whilst increasing the likelihood of repurchasing when compared with non-loyal customers (Bowen & Chen, 2001).

2.5. PREVIOUS STUDIES: CONTRIBUTIONS AND LIMITATIONS

The different models developed and proposed in previous studies allowed for a better comprehension of the attributes that influence the quality of the service provided by hotels according to the perception of customers. In the past, hotels developed satisfaction questionnaires to allow them to grasp the perceptions of consumers but, nowadays, this trend is being replaced by growing online platforms were consumers post their reviews.

The availability of information is extremely useful for academic purposes and allows for generalizations and deeper conclusions. Moreover, the development of big data analytics also facilitates the analysis of millions of reviews without an outstanding number of manual tasks.

The general limitations of the existing models include: (1) the idiosyncrasy of models, since most of them requires adaptations when considering different datasets, platforms or sample; (2) limited samples, since the population considered is most often circumscribed to one city, country or region which may impair the conclusions obtained and the generalizations that can be derived from them; and (3) a limited number of variables which, in turn, reflects the need of a refinement of the model to capture explanatory power of other variables not considered in the existing model. In this sense, the proposed methodology is *sentiment analysis*, since it is of the utmost importance to capture the sentiment in every online review to identify “hidden” attributes that are relevant for consumers and generate positive (negative) perceptions when the expectation are exceeded (defrauded), while allowing for an understanding of which attributes are more or less relevant depending on the hotel category, measured by the number of hotel stars of the hotel. *Table 2* summarizes the method, contributions, and limitations of previous studies.

AUTHOR	METHOD	CONTRIBUTIONS	LIMITATIONS
López Fernández & Serrano Bedia (2004)	*SERVQUAL*	▪ Service quality is a result of meeting customers' expectations rather than the hotel stars itself.	▪ Limited sample. ▪ Model is idiosyncratic.
Ye et al. (2009)	*Log-linear regression*	▪ Importance of online reviews on online bookings. ▪ Introduction of a proxy for the number of online bookings.	▪ Limited sample. ▪ Refinement of the model is needed.
Rhee & Yang (2015)	*Conjoint analysis*	▪ Highlights differences between the relevant hotel attributes for satisfied vs unsatisfied customers. ▪ Total part-worth values (TPWV) analysis allows hotel managers to discover which combinations of attributes provides more satisfaction for customers. ▪ Adaption of conjoint analysis to online reviews, whereas previous studies relied on experimental and survey datasets.	▪ Limited sample. ▪ Missing the combination of content analysis with conjoint analysis. ▪ Hypothetical study that requires empirical validation in the future.
Martin-Fuentes (2016)	*Spearman's correlation, chi square and Pearson's correlation*	▪ Broad sample. ▪ Highlights the relationship between hotel stars and the score attributed by customers on their reviews.	▪ Model is idiosyncratic.

Akhtar et al. (2019)	*Heuristic-Systematic Model (HSM) and Systematic Cues*	▪ Reduction of ambivalence on hotel brands' reputation and review websites derived from divergent data on online reviews	▪ Limited sample (one city). ▪ Limitations derived from the methodologies applied. ▪ Limitations due to the chosen set of data.
Veloso et al. (2019)	*Single Criteria and Multiple Criteria profiling methods*	▪ Presents a new method for profiling approach	▪ Limitations derived from the applied methods.
Giglio et al. (2020)	*ML Algorithms*	▪ Identification of the main attributes that impact costumer's evaluation on a luxury hotel. ▪ Utilization of a new technique to explore the data ▪ The results can be used by the hotel management in order to improve their communication methods	▪ The study only considers the images provided by a tourism platform despite the positive/negative information attached and its weight ▪ Limited sample. ▪ Limitations derived from the percentage error being related to computer science and mathematics progress
Sann et al. (2020)	*Descriptive analyses, independent sample T-tests and one-way analysis of variance (ANOVA) tests*	▪ Identifies different patterns of complaining behavior depending on the cultural background of the customer and hotel stars. ▪ Highlights critical attributes for customers based on the cultural background or the number of hotel stars in which they are staying. ▪ Ample list of nationalities of the consumers allows the authors to generalize.	▪ Limited sample (one city) ▪ Model is idiosyncratic. ▪ Refinement of the model is needed in terms of the attributes considered.
Zhang et al. (2020)	*Multi-stage Multi-attribute decision making methods (MADM)*	▪ It is constructed under the perspective where a client is not a single costumer, rather a long-term partner (i.e. travel agency) ▪ Considers the effect of positive or negative reviews on the psychological aspect ▪ Introduces a new technique	▪ Limitations intrinsic to the methodology used ▪ Only considers online ratings and not reviews ▪ Only considers a single final decision maker

Table 2. Previous studies - methods, contributions, and limitations

3. RESEARCH HYPOTHESES AND CONCEPTUAL MODEL

Each review collected for the purpose of this research includes a rating from 1-5, in the case of TripAdvisor, and 1-10 in the case of Booking.com and the opinion written in text by the reviewer. Each text includes one or more positive or negative opinions that influence the overall sentiment of the review.

Martin-Fuentes (2016) argues that the user satisfaction is positively influenced by the hotel category, that is, the number of stars attributed to each hotel. Therefore, this study hypothesizes the following:

H1: The higher (lower) the hotel category, the higher (lower) the rating of the review and the better (worse) the sentiment of the review.

Alvarez & Hatipoğlu (2014) found that, depending on the nationality of the reviewer, the positive and/or negative feedback provided will differ. Moreover, the authors posit that the attributes valued by the guests also differ depending on their nationality. In another research, Ngai et al. (2007) found differences in the complaint behavior between Asian and non-Asian guests, asserting that Asian guests are more likely to engage in private complaining when compared with non-Asian guests, therefore tending to be less vocal and persistent about their complaints. The key insight, as the authors posit, is the influence that culture has on the complaint behavior. Finally, Kim et al. (2018) also found differences in the reviews posted by customers from different cultural backgrounds, asserting that Westerners' reviews tend to be more positive and analytical and that guests from the United States tend to value more the opinions from their compatriots. Based on these studies, this research also hypothesizes the following:

H2: The sentiments expressed in the review depend on the nationality of the reviewer.

The last hypothesis of this research stems from the work developed by Mellinas et al. (2015), where the authors find that Booking.com employs a 2.5-10 scale (*Figure 7*) rather than a 1-10 scale (Martin-Fuentes et al., 2018b; Mariani & Borghi, 2018), which inflates the scores of the hotels (Mellinas et al., 2016).

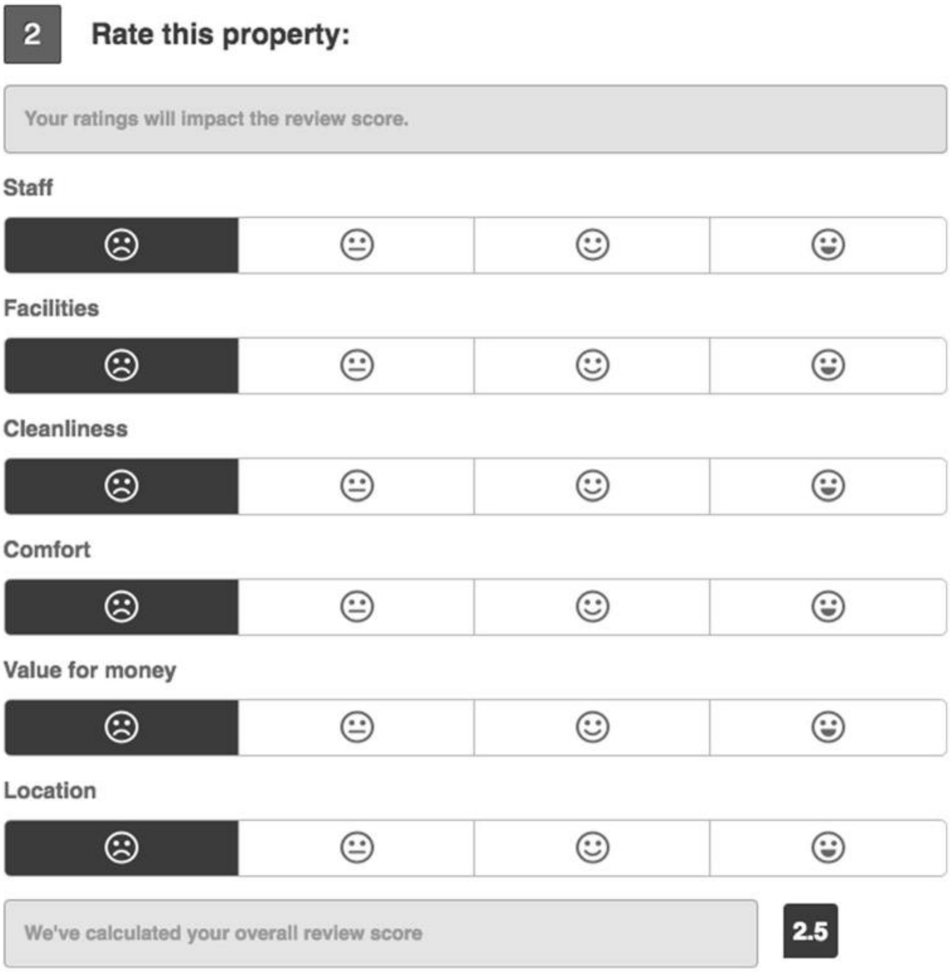

Figure 7. Form to rate accommodation in Booking.com
Source: Martin-Fuentes et al., 2018b

Moreover, this inflation is more significant in hotels with lower scores (Mellinas et al., 2016), fact that was proven by Mariani & Borghi (2018) in a complementary research where the authors confirmed the left-skewness of the review scores on Booking.com. Moreover, the authors also assert that the distribution is more left skewed as the hotel category increases. Therefore, the last hypothesis of this research is the following:

H3: The sentiment in Booking.com and TripAdvisor is expected to be the same. However, the review ratings in Booking.com are expected to be higher.

The research hypotheses will be texted using Semantria, a sentiment analysis software from Lexalytics. The software includes an Excel plugin that uses the reviews previously consolidated into a single *.CSV* file to perform the analysis. Each review is a document and the sentiment conveyed through the review is classified as negative, neutral, or positive (Widerstedt et al., 2018).

According to the software properties, a document is considered negative when the sentiment score is smaller than -0.05. As opposed, a document is considered positive when the sentiment score is higher than +0.22. Finally, the document is neutral when the sentiment ranges between -0.05 and +0.22 (Lexalytics, 2020a). *Table 3* shows the scale used in Semantria.

Sentiment	Range
Negative	< -0.05
Neutral	[-0.05 – 0.22]
Positive	> 0.22

Table 3. Default sentiment scale used in Semantria

Semantria also includes industry packs as features. Industry packs are industry-specific dictionaries developed to improve the overall assessment of the sentiment in content related with each specific industry (Lexalytics, 2020b). For this research, the Hospitality – Hotels industry pack was used in Semantria's plugin for Excel.

Figure 8 presents the conceptual model developed for this research.

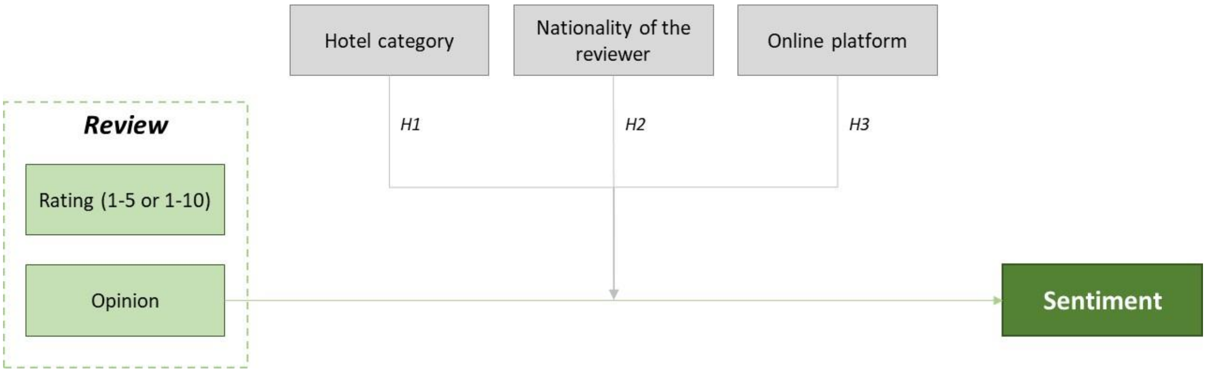

Figure 8. Conceptual model

4. METHODOLOGY

In the previous chapter, this study framed the importance of online reviews in the consumer decision-making process when booking a hotel nowadays and how the hotel star-classification system might be losing credibility as it focuses mainly on infrastructural requirements of the buildings.

The existing literature mainly focus on approaches from a quantitative perspective, that is, the relationship between the hotel category and the reviews is established based on the score attributed by the reviewer.

The objective of this study is to understand if the hotel star-classification system in place in Portugal reflects the opinions expressed in online reviews by consumers. Moreover, the study also aims to understand the impacts of the nationality of the reviewer in the sentiment conveyed through the review and to test if there are significant differences between the two platforms considered in this research – TripAdvisor and Booking.com.

Since Portugal is not a member of the Hotelstars Union, this research can contribute to measure if there is a need for the country to adjust the existing criteria or if, on the other hand, the criteria applied correctly reflects the perspective of the consumers.

The present chapter starts with the definition of the population and sample to be considered in the study, before presenting the data collection and data analysis processes. The data analysis section includes a brief introduction to *Natural Language Processing* and *Sentiment Analysis* and finishes with the conceptual model developed and the research hypotheses to test.

The sample of this study encompasses 192 Portuguese hotels located in Lisbon and included in *Registo Nacional de Turismo*.

4.1. POPULATION

The population of this study comprises the customers of the hotels located in Lisbon included in *Registo Nacional de Turismo* (*RNT*). The platform includes mandatory information about relevant tourism entities in the country (e.g. hotels, travel agencies, etc.) and must be filled and updated by the entities themselves (Turismo de Portugal, 2020b).

The information about the authorized hotels located in Lisbon was extracted from *Registo Nacional de Turismo*. The output extracted from the database included all the hotels registered until 31/12/2019 - a total of 204 hotels.

Figure 9 shows the distribution of the 204 hotels per star category.

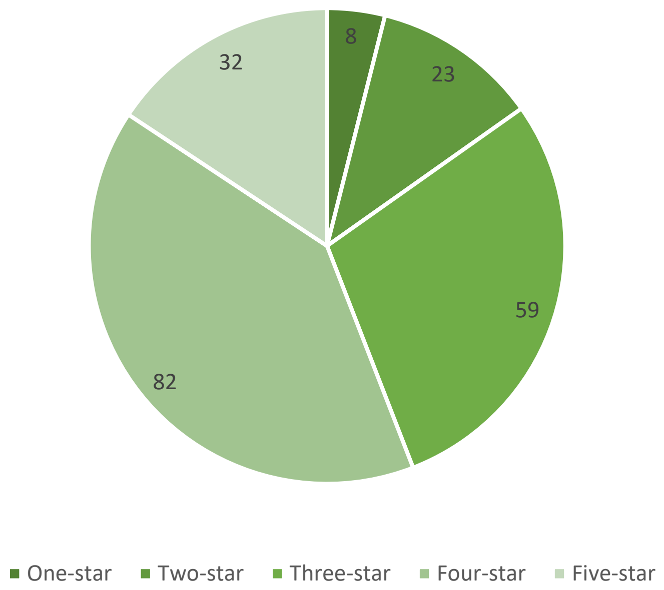

Figure 9. Distribution of hotels located in Lisbon per star category
Source: Turismo de Portugal, 2020b

4.2. SAMPLE

The sample considered in this study comprises the opinion of hotel guests from Portuguese hotels located in Lisbon and included in *Registo Nacional de Turismo*. This study analyzes the reviews posted in 2019 in both Booking.com and TripAdvisor, two of the leading tourism websites around the world.

Booking.com is an Online Travel Agency (OTA) and is also considered to be the world's main service in hotel reservation (Mellinas et al, 2016; Mariani and Borghi, 2018). The platform includes a comprehensive number of costumer's reviews that can be used as eWOM by future guests (Martin-Fuentes, 2016). This online platform is part of Priceline Group (Mellinas et al, 2016), being available in over 43 different idioms with an offer above the 29 million accommodations in more than 2.5 million properties (Booking.com, 2020a). Booking.com is present in over 225 countries with beyond than 1.5 million reservations per day (Booking.com, 2020b).

TripAdvisor is, on the other hand, one of the top players on web-based consumer opinion platform (COPs) (Martin-Fuentes, 2016). It has 463 million visits per month on average that find over 860 million reviews on more than 8.7 million accommodations, restaurants, airlines, cruises, and other experiences to make the best of their trip. This platform is accessible in 49 markets in 28 different idioms with the objective to spread eWOM and help customers when planning a trip (TripAdvisor, 2020).

According to Martin-Fuentes et al. (2018b), the classification system in Booking.com and TripAdvisor is different. In Booking.com, the rating is calculated by considering the mean of six individual dimensions (*Figure 7*), whereas in TripAdvisor the score is attributed directly and the individual dimensions can be evaluated independently afterwards, not being taken into account for the final score.

To define the complete sample of this study, all the reviews from 2019 written in English were extracted from both TripAdvisor and Booking.com, following the process detailed in the next section – *3.3. Data Collection*. After the extraction from *RNT*, the hotels reviewed by customers in both platforms were compared and the ones with no correspondence in one of the platforms were removed. Therefore, 12 hotels were eliminated and led to a final dataset of 38,292 reviews from 192 hotels.

4.3. Data Collection

The data collection process used in this study comprises the extraction and compilation of online reviews from Booking.com and TripAdvisor for the selected sample. A Python script was developed using Anaconda ® - an open source software with over 20 million users around the globe (Anaconda, 2020) – to *web scrape* every URL. Dewi et al. (2019) define *web scraping* as any method used to extract information from the Internet, instead of performing the task without resorting to automation (Vargiu & Urru, 2013). The key benefit is that unstructured data can then be structure and liable to be worked and explored in databases (Vargiu & Urru, 2013; Dewi et al., 2019).

The first step is to identify the URL of the hotel in both platforms. Second, the Internet pages must be *web scraped* using a Python script in Anaconda ® and the results are exported into an individual *.CSV* file per platform. Finally, the individual files must be compiled into a unique *.CSV* file that comprises the final dataset. The script uses BeautifulSoup, a Python library to retrieve data from HTML.

For this research a single dataset was prepared including the reviews written in English in both platforms in 2019 for the 192 hotels included in the sample.

The variables to be extracted from both platforms are the following (*Table 4*):

Variable	Description
Hotel name	The name of the hotel.
Hotel location	The location of the hotel.
Hotel rating	The overall rating of the hotel in the platform. The rating ranges from 1-5 in TripAdvisor and 1-10 in Booking.com.
Number of reviews	The total number of reviews in the platform.
Language of the review	The language of the review. This variable is retrieved to ensure that only reviews written in English are extracted.
Date of the review	The date when the review was posted.
Author of the review	The author of the review.
Nationality of the reviewer	The nationality of the reviewer.
Rating of the review	The overall rating of the review.
Title of the review	The title of the review.
Body of the review	The content of the review. Only reviews with text written in English were extracted.

Table 4. Variables to extract from Booking.com and TripAdvisor

The first two variables – hotel name and hotel address – will be used to crosscheck the information between *RNT*, TripAdvisor and Booking.com. After assuring the correspondence between the three sources, the hotel category and city obtained in *RNT* shall be considered in the analysis.

The hotel rating in Booking.com ranges from 1-10 whereas the hotel rating in TripAdvisor ranges from 1-5. Given that the ratings used in TripAdvisor and Booking.com differ, this research will normalize the ratings (Martin-Fuentes et al., 2018b) to ensure a comparability between both scales. The normalization was performed using a Python script and the *Scikit learn* library.

Figure 10 schematizes the process described above, from the *web scraping* to the final dataset to be used in the analysis.

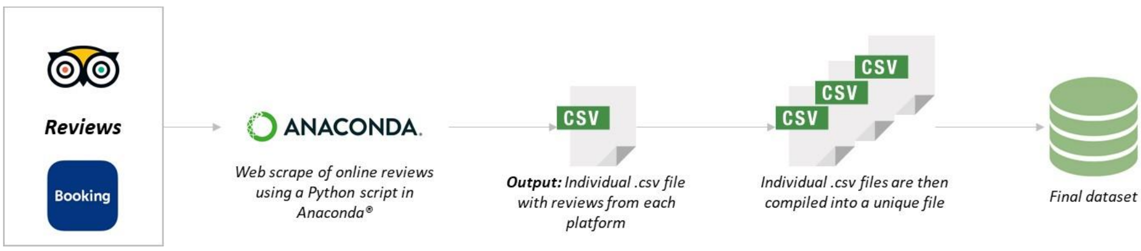

Figure 10. Data collection process

The model defined in the following section will be applied to the dataset and the conclusions drawn in the next chapter.

4.4. Data Analysis

4.4.1. Natural Language Processing

Natural Language Processing (NLP) encompasses the techniques used to analyze and manipulate the human language using computers (Liddy, 2001; Collobert & Weston, 2008; Bird et al., 2009; Goldberg, 2017).

Its origin traces back to the 1950s and results from a combination of two fields of study: artificial intelligence and linguistics (Nadkarni et al., 2011). NLP was first applied to simple translation problems where the researchers tried to translate short sentences into other languages. Their efforts were overthrown by words with multiple meanings (e.g. bank), leading to disastrous translations (Brill & Mooney, 1997; Liddy, 2001; Nadkarni et al., 2011). The book *Syntactic Structures* published in 1957 by Noam Chomsky, largely contributed to linguistics, as the author claimed one can analyze a sentence from the syntactical structure standpoint without considering its semantic, that is, its meaning. The now infamous sentence from the book - *Colorless green ideas sleep furiously* - is an example of a sentence with no practical meaning, but grammatically well formed (Jackson & Moulinier, 2002; Chomsky & Lightfoot, 2002). With Chomsky's work researchers understood, for the first time, how linguistics could help in this process of translation (Liddy, 2001).

In the following decades, the progress kept focusing on using hand-coded information used by computers to decipher the human language. Systems that relied on hand-coded information required an enormous quantity of rules to help the systems to decipher the peculiarities of the human language (e.g. which verbs can be applied to which nouns) (Nadkarni et al., 2011) and only served the purposed they were developed for (Brill & Mooney, 1997).

Closer to the end of the millennium, the focus shifted to machine learning and statistical methods where algorithms were developed and trained with corpora (set of texts around a certain topic) to promote self-learning and pattern identification (Brill & Mooney, 1997; Nadkarni et al., 2011). In fact, particularly in the 1990s, NLP interest and work rose sharply. Computers were then endowed with better processing capacities and the availability of texts in an electronic format also increased. To support all these improvements, the Internet was also emerging (Liddy, 2001). This period marks the emergence of *Statistical NLP*, replacing the existing hand-coded information systems. If, in the past, systems relied on a heavy set of rules (e.g. grammar rules) to evaluate whether a sentence is correct or not, *statistical NLP* allowed systems to navigate through several texts and derive the rules to apply from these texts (Jackson & Moulinier, 2002) attributing a probability for each sentence and providing the results based on the defined probabilities. As systems receive more data, they improve their pattern recognition and become more reliable (Nadkarni et al., 2011).

The ultimate goal of *NLP* is to understand the human language, but the path is still being drawn and systems still require improvements in order to reach it (Liddy, 2001; Collobert & Weston, 2008). Nevertheless, existing systems already can perform tasks like translating a text or answering and explaining the key ideas within a text (Liddy, 2001).

4.4.2. Sentiment Analysis

Sentiment analysis (SA), also called *opinion mining* (OM), analyzes people's opinions, evaluations and emotions towards products, services, or organizations (Liu, 2012; Medhat et al., 2014; Kazmaier & van Vuuren, 2020). It aims to capture the true sentiment within the texts people write to express themselves (Wilson et al., 2005; Al-Natour & Turetken, 2020). Although *sentiment analysis* is a sub-field of *Natural Language Processing*, their history is quite disparate as the first only started to emerge before the start of the new millennium, while the latter has decades of history and applications (Liu, 2012).

There is a general agreement that SA and OM are interchangeable terms for the same definition (Pang & Lee, 2008; Liu, 2012; Medhat et al. 2014; Ravi & Ravi, 2015; Kazmaier & van Vuuren, 2020), although Tsytsarau & Palpanas (2012) provide distinct notions for both terms. From an historical standpoint, according to Pang & Lee (2008) and Liu (2012), SA and OM appeared in the literature in the same year, although in different studies – Nasukawa and Yi (2003) and Dave et al. (2003), respectively. Nevertheless, it is also worth to notice that previous research on sentiments and opinions had already been conducted since the beginning of the millennium, prior to the terms being coined in the above mentioned papers (Pang & Lee, 2008; Liu, 2012).

Sentiment analysis is a broad subject that can be applied to almost every area of our lives (Liu, 2012), which creates a business opportunity for several companies in the world (Pang & Lee, 2008). In the past, companies used to develop and distribute surveys to capture consumers' opinions, while consumers used to rely on a narrow circle of contacts to obtain opinions about a given product or service. Nowadays, this information is widely available in the Internet and the problem is not on how to obtain relevant information from multiple sources, but rather how to process that information in a comprehensive and useful way. Thus, the need for *sentiment analysis* systems (Liu, 2012).

SA can be applied to consumer's reviews to obtain feedback from what can be improved by the seller to ensure a better consumer buying experience, to measure the positioning and notoriety of a certain brand and to identify opportunities for new products or services in the market. Politics can benefit from sentiment analysis by analyzing the public's opinion regarding a certain policy or the upcoming elections. Financial markets can also use sentiment analysis to predict how certain stocks will perform, based on the opinions of various stakeholders. Other relevant applications include box office prediction and recommendation systems (Pang & Lee, 2008; Liu, 2012; Medhat et al., 2014; Ravi & Ravi, 2015; Al-Natour & Turetken, 2020; Kazmaier & van Vuuren; 2020).

5. RESULTS AND DISCUSSION

In the previous chapter, the sample of this study was defined along with data collection and data analysis processes. The proposed research hypotheses are tested in the present chapter that begins with an overview on the composition of the sample and the scores obtained from the analysis. Following this overview, each hypothesis is individually assessed and the adequate statistical analysis, in line with the existing literature, are developed to test whether the proposed hypothesis holds in the defined sample. The chapter ends with a summary table on the results of the proposed hypothesis.

In line with Ghasemi & Zahediasl (2012), in the case of large samples, according to the central limit theorem the distribution of the data tends to be normal. Therefore, this research assumes the normality of the data in each of the statistical analysis performed.

The sample comprise 38,292 reviews in 192 hotels located in Lisbon, Portugal. *Table 5* summarizes the data compiled for this research.

	Booking.com	TripAdvisor
Number of reviews	27,289	11,003
Min. reviews per hotel	8	1
Max. reviews per hotel	866	499
Avg. reviews per hotel	142.87	57.61
Number of nationalities of the reviewers	112	109

Table 5. Sample structure

The number of reviews posted in Booking.com is 2.48 times higher than the reviews in TripAdvisor. This is an expected result since the Booking.com approach to stimulate reviews is more intrusive, as highlighted by Martin-Fuentes et al. (2018b). Moreover, in Booking.com the minimum number of reviews per hotel is 8, whereas in TripAdvisor that number is 1. In this research, the reviewers are native from 131 different countries, 87 of which are shared in both platforms. In TripAdvisor, there are 110 different nationalities among the reviewers, 3 countries less than in Booking.com. In 2,672 reviews, the nationality of the reviewer was not available.

Figure 11 presents the decomposition of the sentiment of each review per hotel category in TripAdvisor, whereas *Figure 12* presents the same data for Booking.com.

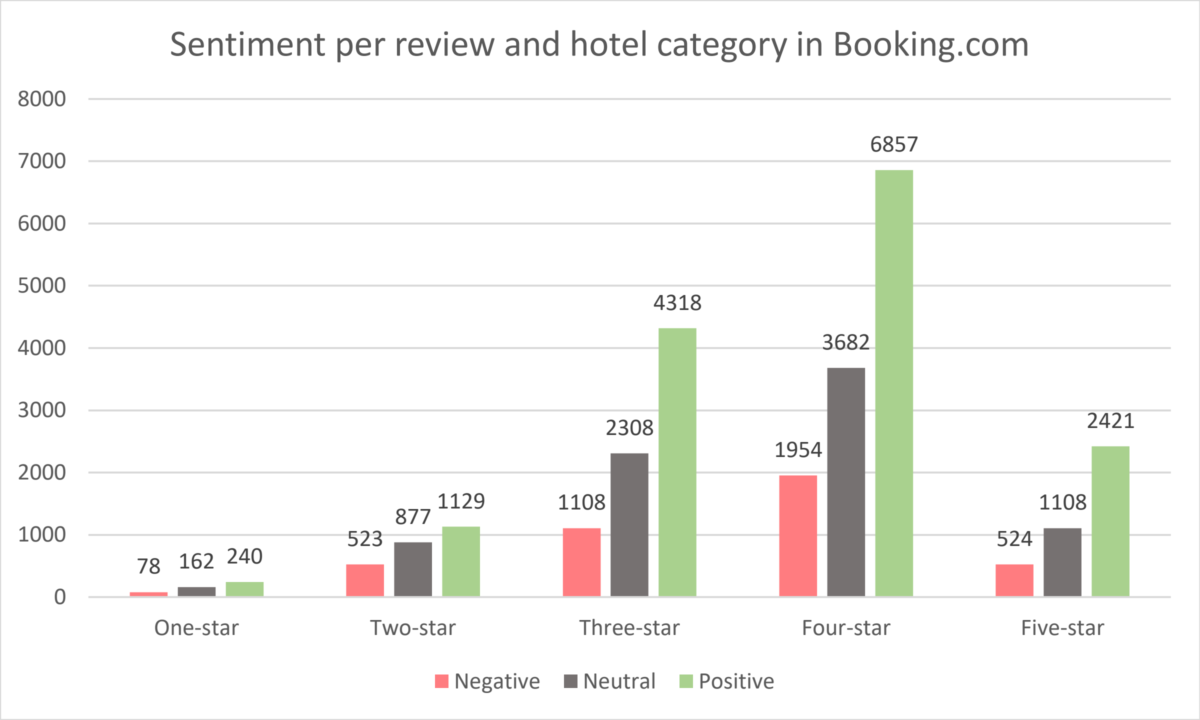

Figure 11. Sentiment (positive, neutral, negative) per review and hotel category in Booking.com

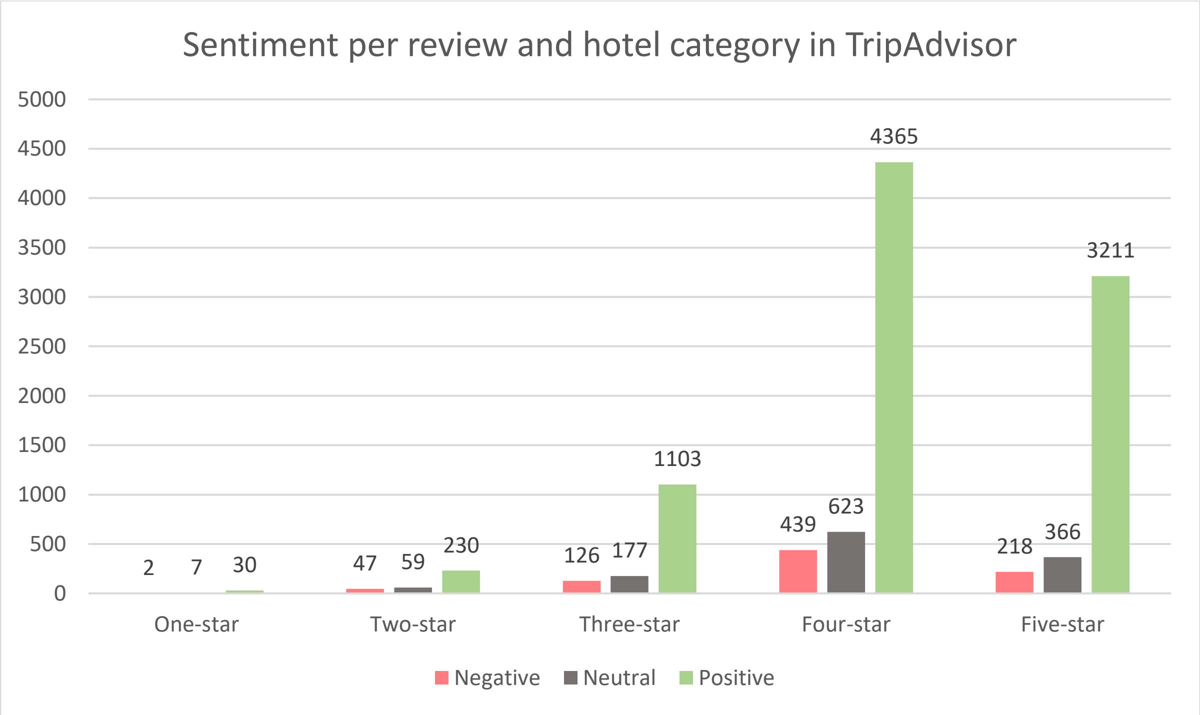

Figure 12. Sentiment (positive, neutral, negative) per review and hotel category in TripAdvisor

The sentiment score in this research ranges from -1.875 to 2.59. In TripAdvisor, the lowest sentiment score is -1.875, whereas the highest is 1.83. In Booking.com, the values are -1.56 and 2.595, respectively.

In TripAdvisor, 81,24% of the reviews show a positive sentiment, whereas neutral and negative sentiment represent 11,20% and 7,56%, respectively, of the total number of reviews analyzed for that platform. In Booking.com, the negative sentiment represents 15,34% of the total reviews in that platform and the neutral and positive sentiment represent 29,82% and 54,84%, respectively. The results align with Zervas et al. (2015), who acknowledged the high number of positive reviews in online platforms.

The results from the sentiment analysis performed in Semantria are summarized in *Table 6*.

Hotel category	*	**	***	****	*****	TOTAL
Booking.com						
Number of reviews	480	2529	7734	12493	4053	27289
% of total reviews	1.25%	6.60%	20.20%	32.63%	10.58%	71.27%
Avg. rating of the review	8.2733	8.1216	8.7076	8.7091	8.9633	8.6843
Avg. rating of the review (normalized)	0.8081	0.7913	0.8564	0.8566	0.8848	0.8538
Avg. sentiment	0.2094	0.1847	0.2561	0.2517	0.296	0.2526
Standard deviation	0.3333	0.3565	0.3355	0.3571	0.3635	0.3526
TripAdvisor						
Number of reviews	39	336	1406	5427	3795	11003
% of total reviews	0.10%	0.88%	3.67%	14.17%	9.91%	28.73%
Avg. rating of the review	4.2564	3.8631	4.2055	4.3706	4.5676	4.4015
Avg. rating of the review (normalized)	0.8141	0.7158	0.8014	0.8426	0.8919	0.8504
Avg. sentiment	0.4225	0.3088	0.3764	0.4071	0.4526	0.4159
Standard deviation	0.2659	0.3226	0.2974	0.2922	0.2782	0.2908
Total						
Number of reviews	519	2865	9140	17920	7848	38292
% of total reviews	1.36%	7.48%	23.87%	46.80%	20.50%	100%
Avg. rating of the review	-	-	-	-	-	-
Avg. rating of the review (normalized)	0.8086	0.7824	0.8479	0.8523	0.8882	0.8528
Avg. sentiment	0.2255	0.1992	0.2746	0.2988	0.3717	0.2995
Standard deviation	0.3333	0.3549	0.3327	0.3462	0.3343	0.3441

Table 6. Detailed results about the reviews and document sentiment per hotel category

The average rating of the review for the total sample, cannot be computed due to the different scales employed by Booking.com and TripAdvisor. Therefore, only after the normalization, the average rating of the review can be computed.

According to the results, the sentiment of the reviewer has different behaviors in the two platforms. In both platforms, the five-star hotels are the ones with higher average sentiment in a review: 0.296 and 0.4526 in Booking.com and TripAvisor, respectively. Notwithstanding, in Booking.com the three-star hotels are ranked second in terms of the average sentiment, followed by the four and one-star hotels. In both platforms, the two-star hotels scored the worst in terms of average sentiment. In TripAdvisor, the one-star hotels are the second in terms of average sentiment, followed by the four and three-star hotels, respectively.

Two one-way ANOVA (López Fernández & Serrano Bedia, 2004; Martin-Fuentes et al., 2018a) were performed to measure whether there were statistically significant differences between the means of the hotel categories in terms of the sentiment score and the review rating after normalization. The results show that, with a confidence level of 99% ($p < 0.01$), there are statistically significant differences between the hotel categories in terms of the sentiment score and the review rating, allowing us to reject the null hypothesis that the mean score of the five different hotel categories is equal – $F(38287,4) = 168{,}0456$, $p = 6{,}6700^{-143}$ and $F(38287,4) = 175{,}71943$, $p = 1{,}9738^{-149}$, respectively. The output from both analyses are included in *Tables 7* and *8*.

ANOVA*sentiment*

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	78.2067	4	19.5517	168.0456	6.67E-143	3.3197
Within Groups	4454.5936	38287	0.1163			
Total	4532.8003	38291				

Table 7. Results from ANOVA - sentiment per hotel category

ANOVA*review_rating*

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	25.2771	4	6.3193	175.7194	1.97E-148	3.3197
Within Groups	1376.8886	38287	0.0360			
Total	1402.1657	38291				

Table 8. Results from ANOVA - review rating per hotel category

Therefore, **H1 is partially accepted**. We can assert that there are statistically significant differences between the hotel categories in terms of sentiment and review rating. Moreover, the hotels from the highest category, are the ones with the highest average sentiment. However, the average sentiment does not increase consistently with the hotel category. The findings of this study seem to align with the research from López Fernández & Serrano Bedia (2004), where the authors assert that the quality of service is not measured by the hotel category, but by meeting the customers' expectations.

To test H2, this research maps each country with a region – America (AME), Asia and Pacific (ASP), Europe (EUR) and Middle East and Africa (MEA) – following the approach proposed by Banerjee & Chua

(2016). Moreover, a single factor ANOVA was used to test whether there are statistically significant differences between the mean score of each of the regions. The results of the analysis are summarized in *Table 9*.

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	28.6962	3	9.5654	81.3907	1.80E-52	3.782
Within Groups	4185.7556	35616	0.1175			
Total	4214.4518	35619				

Table 9. Results from ANOVA performed to test H2

The results show that, with a confidence level of 99% ($p < 0.01$), there are statistically significant differences between the mean scores of each region in terms of sentiment score, allowing to reject the null hypothesis that the mean score for each region (AME, ASP, EUR, MEA) is equal – $F(35616,3) = 81,3907$, $p = 1,8018^{-52}$. **H2 is then accepted**. There are statistically significant differences between the nationality of the reviewer in terms of the sentiment conveyed through the review.

Figure 13 presents the average sentiment score and standard deviation per region. America scores the highest average sentiment whereas Middle East and Africa scored the lowest, albeit scoring the highest standard deviation. The lowest standard deviation is observed in Asia and Pacific.

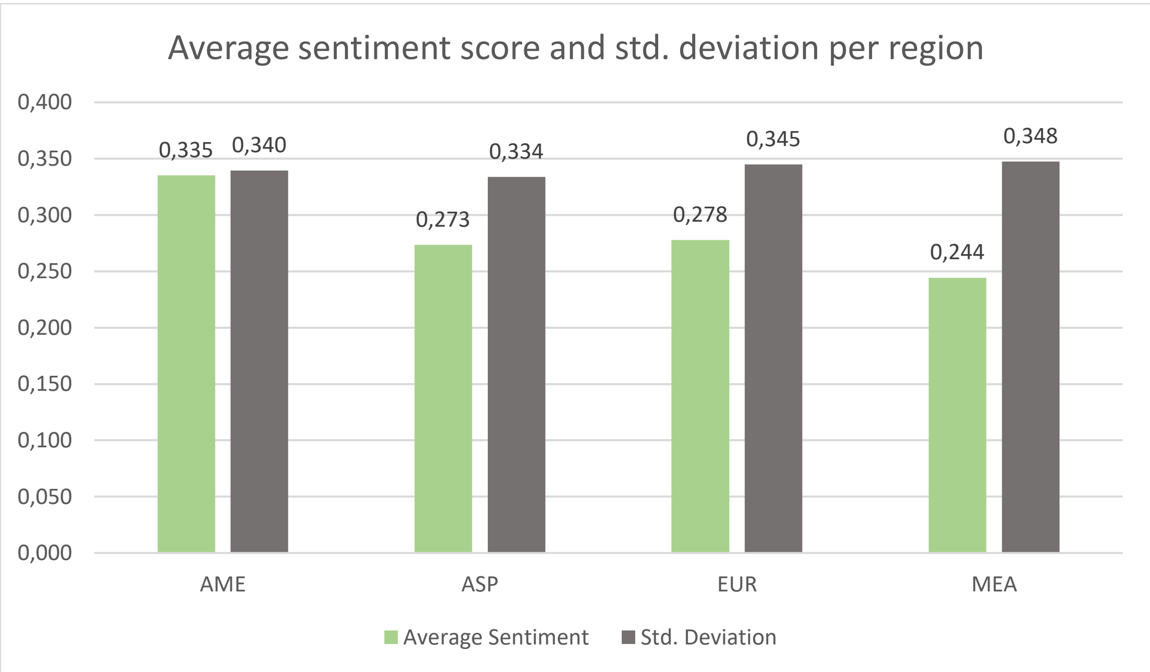

Figure 13. Average sentiment score and standard deviation per region

Finally, **H3** proposes that the sentiment conveyed by the reviewers in both platforms would be the same. Moreover, in line with previous research, the review ratings in Booking.com are expected to be inflated, in comparison with TripAdvisor. In this regard, the first difference worth noticing is that contrary to Bjørkelund et al. (2012) – where in over 600,000 reviews none score less than 2.5 in Booking.com - the dataset used in this research included reviews ranging from 1-10, which might indicate that Booking.com is trying to correct the inflation of the scores within the platform.

Table 6 shows that, except for one and five-star hotels, the review rating after normalization is higher in Booking.com than in TripAdvisor. Moreover, the sentiment in TripAdvisor is always higher than in Booking.com – approximately, 1.64 times more, on average. In the case of one-star hotels, albeit the sentiment in TripAdvisor is 101% higher than in Booking.com, the average review rating after normalization is only 0,74% higher. In two-star hotels, although the average sentiment is 67% higher in TripAdvisor, the review rating is 9.54% smaller than in Booking.com.

Following the approach used by Martin-Fuentes et al. (2018b), a *Student's t* test was performed considering the scale after normalization in both platforms. The obtained results, contrary to Martin-Fuentes et al. (2018b) do not allow this research to reject the null hypothesis that both means are equal. Therefore, this research found no statistically significant evidence that the ratings from Booking.com are inflated. Moreover, in line with the previous finding regarding reviews with a score lower than one in Booking.com, the results might indicate that Booking.com is trying to correct their scores inflation. **H3 is then rejected**. Nevertheless, it is worth noticing that the sentiment conveyed through the reviews is higher in TripAdvisor by 65%, approximately, which might indicate that the sentiment and the review rating are not aligned. *Table 10* includes the results of the test.

	Booking.com	*TripAdvisor*
Mean	0.8538	0.8504
Variance	0.0281	0.0577
Observations	27289	11003
Hypothesized Mean Difference	0	
df	15508	
t Stat	1.36829	
P(T<=t) one-tail	0.08562	
t Critical one-tail	1.64495	
P(T<=t) two-tail	0.17124	
t Critical two-tail	1.96012	

Table 10. Results of the Student's t-test

Table 11 summarizes the outcome of each hypothesis present in this research.

Hypothesis	Result
H1: The higher (lower) the hotel category, the higher (lower) the rating of the review and the better (worse) the sentiment of the review.	Partially accepted
H2: The sentiments expressed in the review depend on the nationality of the reviewer.	Accepted
H3: The sentiment in Booking.com and TripAdvisor is expected to be the same. However, the review ratings in Booking.com are expected to be higher.	Rejected

Table 11. Outcome of the hypothesis in this research

6. CONCLUSIONS, LIMITATIONS AND RECOMMENDATIONS FOR FUTURE WORKS

This research included three major objectives: to measure if the hotel category influences the review rating and the sentiment of the reviewer, to measure if the sentiments expressed depend on the nationality of the reviewer and to measure whether the review ratings in Booking.com are inflated in comparison with TripAdvisor.

Regarding the first objective, there are statistically significant differences between the different categories in terms of the sentiment expressed in the review. However, contrary to what was hypothesized, the sentiment does not increase as the hotel category increases. The findings seem to align with López Fernández & Serrano Bedia (2004), who claim that the quality of the service provided depends more on meeting customers' expectations than on providing a luxury experience.

This research also found that the sentiment expressed in the reviews depends on the nationality of the reviewer, supporting the previous work from Alvarez & Hatipoğlu (2014) and Kim et al. (2018) who posited the differences in the consumers reviews depending on the nationality and cultural background of the reviewers.

Contrary to Bjørkelund et al. (2012) and Martin-Fuentes et al. (2018b), this study found reviews with a score lower than 2.5 in Booking.com. Moreover, the results obtained in the research are also not aligned with the previous studies (Mellinas et al., 2015; Mellinas et al., 2016; Martin-Fuentes et al., 2018b; Mariani & Borghi, 2018) as it was not possible to prove that the review ratings in Booking.com are inflated in comparison with the ratings from TripAdvisor.

Finally, for hotels located in Lisbon, this research also discovered that more than 80% of the reviews written in English and posted on TripAdvisor convey a positive sentiment, in line with Zervas et al. (2015), whereas only 54% convey a positive sentiment in Booking. Furthermore, the average sentiment is always higher in TripAdvisor than in Booking.com. However, in the case of two, three and four-star hotels, the review rating after normalization (which allows for a comparison between both platforms) is higher in Booking.com.

This study contributes to the existing literature by providing evidence that the sentiment conveyed through the reviews is not directly influenced by the hotel category. It seems to be a variable influencing the sentiment of the reviewer, albeit also appearing not to be the only one. It also contributes to the previous research regarding the differences in the reviews depending on the nationality of the reviewer by providing evidence that the sentiment is influenced by it. Finally, this research relaunches the debate on whether the ratings from Booking.com are inflated or not in comparison with TripAdvisor.

In regard to the managerial implications, this study provides hotel managers two key insights concerning the service provided. First, the focus should be knowing their customers' expectations in order to meet them and, whenever possible, exceed them. Second, the hotel managers should be aware that different nationalities have different reactions. Therefore, the experience provided should be adapted to satisfy the needs of their target audience and adjusted to the difference nationalities and cultural backgrounds of the guests. Moreover, to all other relevant stakeholders, this study does not provide further evidence that Booking.com ratings are inflated, which might help to restore some confidence in the reliability of the scoring system used by that platform.

All methods, models and approaches have their limitations and this study is not an exception to it. This research only considers reviews written in English. Albeit a significant amount of reviews is considered when analyzing the English language, there are also other languages that could be analyzed to depict more comprehensive results (e.g. Portuguese, Spanish, or French). Therefore, a limitation and recommendation for future works is to consider other languages in this research. To develop this work, the researchers could develop individual dictionaries per language to analyze each review in its corresponding language.

The sample of this study only comprises reviews from guests of hotels located in Lisbon. Thus, another recommendation for future works is to broaden the sample to other cities to obtain an extensive result and to understand whether the results hold in other regions of the world or not. Moreover, there is also the opportunity to explore the hypothesis related with the nationality of the reviewer and analyze the differences between individual countries.

Similar to analyzing only reviews written in English, another limitation of this study is that only Booking.com and TripAdvisor were considered. The analysis can be extended to other platforms (e.g. Ctrip).

Finally, and due to the COVID-19 pandemic that affected the world in 2020, another research opportunity would be to understand how the sentiment and the opinion of the consumers was affected by this event. One could, for example, measure the dimensions (e.g. cleanliness) that most influenced the consumers pre- and post-COVID-19 pandemic.

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