# A Multi-Dimensional Data Analytics Model for Quality Assessment in the Hospitality, Leisure and Tourism Sector:

From Unstructured User-Generated Content to Customizable Structured Information

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# ABSTRACT

With the emergence of travel and hospitality web sites, travellers can now access and review information concerning their trips and stays before they travel, through user-generated content that undertakes the role of electronic word-of-mouth (eWOM) (El-said, 2020; Le Wang et al., 2020). The main aim in this Thesis is to examine how unstructured information can be combined with structured data structures derived from formal methods for assessing products and services, and, to research possible extensions of these approaches that might lead to more insightful analytics of the Big Data of Tourism, Hospitality and Leisure. The data set for this case study consisted of eWOM posted by travellers in the area of Crete in this case until 2019.

To achieve this, a new multi-dimensional model is developed that includes all the dimensions found in SERVQUAL, HOLSERV and HOLSERV(+) scales. The model achieves to present the information from different hierarchical levels/groupings. Based on the insights gained from the unstructured content corpus' frequency analysis, additional categorisations were included to improve the model's efficiency. The final proposed model encompasses online user reviews and structured information derived through mail interviews, descriptive statistics aspect-based sentiment analysis, and multi-class classification, resulting in more sophisticated and insightful data analytics.

Among the findings of this research is the proposed novel Online Review Categorization Model, which is compatible with quality assessment scales, and can be applied in the tourism sector. Moreover, the novel framework developed and applied in this thesis which includes machine learning classification, categorization and annotation approach, with multi-dimensional model development, can be customized and applied to other fields that entail unstructured text that is needed to be classified to multi-dimensional categorization.

***Keywords***: Tourists Satisfaction, Big Data Analytics, Crete, online reviews, eWOM, SERVQUAL, HOLSERV plus

*to my Parents,*

*Konstantinos and Eleni*

## DECLARATION

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I declare that the work in this Thesis was carried out in accordance with the regulations of the University of Nicosia. It is a product of my own original work, unless otherwise mentioned through references, notes, or any other statements.

Signed ……………………  Date 24/02/2021

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## Abbreviation Index

| | |
|---|---|
| COPs | Consumer Opinion Portals |
| CR | Critical Realism |
| eWOM | electronic Word of Mouth |
| UGC | User Generated Content |
| WOM | Word of Mouth |
| CNN | Convolutional Neural Network |

# CHAPTER 1. INTRODUCTION AND BACKGROUND

## 1.1 INTRODUCTION

Recent developments in Internet Technology, combined with the increased importance of social networks, have led to the creation of Terabytes of data, frequently referred to as Big Data (Tang, Ma and Luo, 2020; Agarwal and Dhar, 2014). Academic research on Big data transcends many fields such as Education, Business Administration, Hospitality, Leisure and Tourism. The need to process Big Data, hassled to technological advancements that enable faster processing. A common goal in processing such data is to derive users behaviour or to be more precise, tourists' behaviour (Palese and Usai, 2018; Jayathilaka et al., 2020; Tang, Ma and Luo, 2020; El-said, 2020) if the data are related to the Tourism and Hospitality sector. This is translated to constant new possibilities for developing novel data analyzing techniques, through which researchers, companies and organisations can have insights into information not easily obtained otherwise (Sam and Ryan, 2020; Padma and Ahn, 2020; El-said, 2020; Jia, 2020; Yallop and Seraphin, 2020; Bowen and Whalen, 2017). Moreover, correlating big data with "offline" methodologies might elevate the applications and results of technological advancements even more (Tsao et al., 2020; Palese and Usai, 2018; Boon, Bonera and Bigi, 2014).

In the field of Leisure, travellers now have new ways to share their experiences through the use of a large number of different platforms, from platforms found in online travel agencies such as Tripadvisor, Booking.com, HomeAway (Mack, Blose and Pan, 2008), or with restricted access at the accommodation providers (ReviewPro, Brand Karma, TrustYou, and more) (Blomberg-nygard and Anderson, 2016). In particular, publicly accessible travel websites are becoming tools of increasing importance in one's trip decisions. This information is useful to travellers and researchers who now possess additional information sources to unravel the tourists' point of view and concerns. Capturing the travellers' experiences enables researchers to study the elements that can help in optimizing the tourists' satisfaction. In this way, researchers, tour operators, accommodation providers, and local governments achieve more credible planning and better decision-making.

The information existing on the Web is enormous in volume, while at the same time being virtually unstructured, resulting in difficulty both for personal users as for accommodation byproviders and public sectors to extract the required information and analyze it efficiently. Thus, various data mining applications and techniques have been proposed to extract and analyze online reviews (Boon, Bonera and Bigi, 2014, 2014).

For this research, data related to the hospitality sector in the region of Crete, one of the nine (9) regions of Greece, have been collected and analysed. The direct and indirect impact of Tourism in Greece is 30.9% of 2018s GDP (Lambrou and Ikkos, 2020). In 2019, the tourism sector rose by 1.2 billion euros or 12.8% when the country's GDP rose by 3.6 billion euros or 1,9% (Lambrou and Ikkos, 2020). Tourism is essential for the country when it comes to employment as well. It is estimated that in 2018 tourism created 361 thousand jobs (Ikkos, Koutsos and Lambrou, 2019). Crete is the second region in Greece when it comes to travellers' overnight stays. Crete's region is studied separately, since it provides 20.37% of the tourists' receipts from the whole country (€3,60 billion) (Bank of Greece, 2020). In 2019 Crete received 5.287.600 tourists and had 43.256.200 overnight stays (Bank of Greece, 2020). Tourism in Crete creates a direct contribution to Greece's GDP that comes up to 47% (Ikkos, Koutsos and Lambrou, 2019). Thus, it was a guided decision to focus the research on this region's data for mainly two reasons. Firstly, it would provide a representative sample, and secondly, findings and results can directly relate to regional development.

## 1.2 Thesis Statement, Problem Statement and Research Gap

Service quality assessment questionnaires are based on the Expectation Confirmation Theory, that is, the difference between the consumers' perception of the quality of the service provided and the actual service quality they experience. Online reviews (ratings, content, and volume) may also be viewed and explained through Expectation Confirmation Theory (Cheung and Lee, 2012; Hennig-Thurau et al., 2004). Moreover, Lockyer (2005) identifies the existence of a gap between managers' perceptions of what guests need and what guests actually perceive as essential. To bridge this gap, various service quality assessment scales are used (Seth, Deshmukh and Vrat, 2005). Most of these scales have been based on Parasuramans' service quality scale (SERVQUAL), which is split into six basic dimensions, each of which is assessed from statements that correspond to discrete sub-dimensions, developed to give a comprehensive picture of the service quality perceptions of guests. HOLSERV is a scale based on SERVQUAL that has been developed specifically for the accommodation field. In Hospitality, Leisure and Tourism field, the service quality assessment has been taking place in the offline world utilizing the aforementioned scales.

The ease of access to online reviews, and the volume of data existing offer researchers and managers great potential for evaluating service quality. For instance, accommodation managers have been reviewing eWOM for their marketing strategies (Xiang and Gretzel, (2010). Currently, hotel managers continue to use questionnaires to evaluate service quality (Tefera and Govender, 2016; Chaturvedi, 2017). A possible explanation is that online reviews are based on open-ended questions, and therefore, their content can be variant and incomplete. It is being examined if this drawback can be overcome from the supplementary information found in online reviews. Relevant research attempts to focus on extracting, clustering and correlating eWOM information with satisfaction and service quality (Zhou et al., (2014). As this work progresses, a parameter needs to be clarified regarding the autonomous or supplementary nature (providing complete or supplementary information) of online reviews regarding service quality evaluation.

Li, Ye and Law (2013) suggest that online reviews provide more accurate information since open-ended questions leave space to reviewers to give specific and in detail picture of their experiences. Gretzel et al. (2010) have concluded that most of the information identified in online reviews and surveys is overlapping information, although there are a couple of differences. For instance, online reviews are taking place in real-time and are more cost-effective. Boon, Bonera and Bigi (2013) suggest that online reviews cannot replace traditional service quality questionnaires, but hotels should combine both to achieve a better understanding of service quality. Moreover, there is a need to understand the role online reviews play on the service quality measurement system within those organisations (Li, Ye and Law 2013). In other words, the perception of accommodation providers on these tools needs to be investigated.

Based on the above discussion (more details may also be found in Chapter 2), there has been a debate regarding the effectiveness and the autonomy of online reviews as a tool for service quality management. Researching managers' perceptions regarding online reviews and service quality assessment tools could clarify a few of these issues. No published study exists that examines managers' perceptions on these two tools to the author's best knowledge. To reach a better understanding of the field, this thesis will initially address this gap by identifying how hoteliers perceive online reviews compared to traditional surveys. This phase's findings can inform the next steps of the research.

Customers shape their overall perceptions of service quality in the areas that are most important to them (Liu and Park, 2015). Since each individual perception of importance is different, a customer will rarely give a comprehensive review useful to a broad spectrum of travellers. A reviewer rarely provides feedback on all different dimensions encountered in a quality assessment questionnaire.

This problem might be addressed by data mining and the extraction of quality assessment information from a large corpus of online reviews. Furthermore, Berger (2014) suggests that traditional promotional tactics that have been applied to the offline world can provide us with new insights regarding drivers of consumer behaviour. In support of this, Koch and Benlian (2015) mention that very little attention has been given to classic promotional tactics.

The suggestion mentioned above for overcoming the weaknesses of individual online reviews, together with the possibility of identifying satisfaction and service quality information in eWOM has led researchers to work in the extraction of service quality dimensions from those reviews. Specifically, there are a few studies that explore the possibility of correlating upper-level service quality dimensions (Reliability, Assurance, Tangibles, Empathy, Responsiveness) (Gebremichael, 2019; Palese and Usai, 2018; Rus et al., 2019; Ukpabi and Karjaluoto, 2018; Boon, Bonera and Bigi, 2014; Duan et al., 2013; Li, Ye and Law, 2013). To the best knowledge of the author, there is no research focusing on ways to categorize and correlate eWOM unstructured information to categories of the quality assessment scale dimensions. Following that, this Thesis investigates at a survey-sentence-based level, the sub-dimensions provided in questionnaires in correlation to the information from an online reviews' corpus.

Therefore, this Thesis investigates if online reviews can be fitted in quality assessment scales dimensions and sub-dimensions (SERVQUAL, HOLSERV(+)) and proposes a fine granularity multi-dimensional quality assessment model for the Hospitality, Leisure and Tourism Sector that employes user-generated content (UGC) and transforms it to customizable structured information.

Therefore, this Thesis examines quality assessment scales (SERVQUAL, HOLSERV(+)) versus online user reviews and proposes a fine granularity multi-dimensional quality assessment model for the Hospitality, Leisure and Tourism Sector employing user-generated content (UGC) and transforming it to customizable structured information.

## 1.3 RESEARCH AIM AND OBJECTIVES

The present research has a dual aim: to bring together the structured methodologies of the Business Administration for assessing products and services with the almost unstructured approach of online commentaries of tourists in the area of Crete, and, to research possible extensions of these approaches that might lead to more insightful analytics of the Big Data of Tourism. To achieve a complete understanding of the field, the Thesis first investigates hoteliers and hotel managers' opinions in Crete related to survey questionnaires and online reviews as quality assessment methods. Furthermore, it correlates service quality dimensions to unstructured online reviews and then combines the dimensions of the complementary models of SERVQUAL and HOLSERV(+) to produce a more detailed model. Finally, the Thesis develops an enriched model with additional dimensions that are not present in the previous two models, developing a new enriched and more insightful multidimensional model.

| RESEARCH QUESTIONS AND OBJECTIVES |
| --- |
| **MAIN RESEARCH QUESTION** |
| What aspects of quality assessment scales (SERVQUAL, HOLSERV(+)) can be represented by online reviews? |
| **SPECIFIC RESEARCH QUESTIONS** |
| How do hotel managers perceive online reviews in comparison to traditional surveys? |
| How can eWOM reviews be fitted to SERVQUAL, HOLSERV/HOLSERV+ scales dimensions and sub-dimensions? |
| What aspects of eWOM are not included in SERVQUAL and HOLSERV+? |
| Which additional categories rise from frequency analysis? |
| How can the information richness of the newly-developed model be improved, utilizing the missing aspects? |
| How well does the novel-proposed fine-granularity multi-dimensional model fit eWOM? |
| **RESEARCH OBJECTIVES** |
| Identify the opinions of hotel managers on traditional quality assessment tools and online reviews. |
| Comprehend how hotel managers perceive the information sources of service quality assessment scales and online consumer reviews. |
| Get insight into the information that hotel managers retrieve from each tool, mentioned earlier, and their perception and informational needs that might be left uncovered. |

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|---|
| Identify if there is differentiation or overlapping information between service quality questionnaires and consumer reviews on online travel platforms. |
| Develop a multi-level model to fit eWOM content to the Service Quality Scales categorisation in an upper level to a sentence-based level. |
| Research the possibility of underrepresented categories of SERVQUAL, HOLSERV(+) models |
| Use machine learning to fit online reviews in SERVQUAL and HOLSERV(+) categorisation |
| Perform FrequencyAnalysis on extracted online reviews and identify if there is additional quality assessment information provided from online reviews that is not captured in surveys. |
| Improve the proposed model by adding aspects based on the frequency analysis findings. |
| Apply the novel-proposed fine-granularity multi-dimensional model on eWOM reviews and discuss findings. |

## 1.4 SIGNIFICANCE OF THE STUDY

This study adds to many different research fields (i.e., Hospitality, Leisure and Tourism, Marketing, Retailing) that deal with the quality of services and products, and it can deepen the understanding of the aspects of information that is not usually included in online reviews, by researching hoteliers' and managers' opinions on quality assessment questionnaires in relation to online reviews. Furthermore, the research gives insight into the correlation of quality assessment surveys with online review, by developing a model where user-generated content can be classified into the dimensions and subdimensions of quality assessment scales. Moreover, the thesis identifies more dimensions that have not been captured by the aforementioned tools. Specifically, through descriptive analysis, it explores the possibility of incorporating essential dimensions that improve the model's explantory ability. Then, by utilizing the findings of the insights of the email interview, the initially developed model, and the frequency analysis, the thesis moves on to suggest a novel multi-dimensional model of categorizing and viewing the information. Finally, through this research, a framework arises, that can be applied to Hospitality, Leisure and Tourism, and many different fields that incorporate unstructured text corpus and survey tools, developing specific-to-field customizable models. Having a standardized methodology of collecting and processing data leads to more easily administered and viewed analytics in those fields.

## 1.5 Limitations

A limitation of this research is that it is oriented in information from the region of Crete. Crete accommodates many business travellers and is also a popular touristic region of Greece, especially during the summer period attracting guests from all around the world, providing a culturally diverse the sample that ensures the study's validity. Nevertheless, additional study of other regions, touristic and non-touristic ones, would reinforce the model's validity. When it comes to the first study, the information gathered has provided details that allowed useful insights regarding managers' perspectives on quality assessment methods. In qualitative research based on interviews, it is not uncommon to have fifteen or fewer participants. Still, more research with accommodation providers from different regions would add to the validity of this study. Additionally, the methodological approach of email interviewing made it challenging to re-approach the participants to ask for additional details. In this study, it was not possible, mainly due to participants' lack of time, to engage in person or through a Skype interview session.

The approach to quality assessment processes that review providers have is apparent through the forms and analytics they provide. Nevertheless, it would be interesting to have their perception of quality assessment dimensions. Although repeated attempts have been made to approach providers (including TripAdvisor and Booking.com), there was no response.

## 1.6 Overview of the Thesis

The Thesis consists of five chapters:

**Chapter One** defines the research area and the regional area of study. It offers a first look at the research gap and introduces the research problem and the aim and objectives. In addition, it presents the significance and limitations of this Thesis. The last section of the Chapter outlines the structure of the dissertation.

**Chapter Two** provides the literature review method and introduces a preliminary work that initially led to this research. The next section details the research's theoretical foundations, providing the extant theories on Satisfaction, Service Quality, and electronic word of mouth. Next, the focus shifts to the research's literature framework, investigating word of mouth and its relation to electronic word of mouth. Thereupon, it provides insight into electronic word of mouth and its characteristics and importance in Tourism. Then, the literature review investigates negative and positive eWOM and reviewers' incentives to give an evaluation. Finally, it researches the adoption and generation of service quality scales and the transition from SERVQUAL to HOLSERV+ models.

**Chapter Three** presents the Research Aim and Objectives as well as the Research Questions. Next, the Philosophical Stand of the Thesis is discussed before focusing on the studies' methodological approaches. The study related to managers' perceptions is undertaken email interviews, while content analysis is being incorporated to analyse and synthesise the results. The data mining study uses data mining techniques to extract and analyze the online reviews corpus. A machine learning algorithm is developed to tackle the classification problem, while SEMEVAL's categorisation approach is used to develop the training dataset, which will train the algorithm in order to achieve the classification of the corpus into the newly developed categorization scheme that includes SERVQUAL and HOLSERV(+) dimensions. Descriptive analysis is undertaken in order to identify missing parameters from the models. Then, the convolutional neural network is further customized based on the descriptive analysis results to develop and analyze the novel proposed model that is providing the Thesis with multi-dimensional results.

**Chapter Four** presents the results for both studies. Initially, it presents the perceptions of accommodation providers chosen quality assessment tool. Moreover, it provides their views on the completeness of the information provided from each tool and presents their views on how each tool affects the company's profitability and efficiency. It also discusses the managers' views on the quality and reliability of each tool. At the end of the study's results, a section with conclusions on this study results is presented. The next section presents the results of the data mining processed models. The initial categorization of the proposed model is developed using Almagrabi et al. (2018) approach regarding corpus analysis approach and Pontiki et al. (2016) annotation system. The initial model's dimensions results are discussed before continuing with the corpus's descriptive analysis. The newly emerged categories from the descriptive analysis are discussed, and a new multi-dimensional model is developed, analyzed, and discussed. The Chapter ends with the conclusions of the second study.

**Chapter Five** brings together the main conclusions of both studies. Furthermore, it discusses the limitations of the studies and considers future research possibilities.

# CHAPTER 2. LITERATURE REVIEW

## 2.1 INTRODUCTION

Chapter one presented an introduction of the Thesis and laid down an overview of the research gap, thesis problem and statement, and the structure of the rest of the Thesis. Chapter two presents in detail the method of the literature review, a preliminary work, and the theoretical framework of the Thesis. This Chapter presents the literature review regarding the quality assessment scales, online user-generated reviews and machine learning, their theoretical background, and the extant literature on the fields. This work leads to the research gap and the multi-dimensional model development, as presented in the thesis statement.

First, the methodological approach of the literature research is presented and next, the preliminary work which took place during the first months of the research is presented, and possible alternative directions of the research are investigated. Finally, the specific path has been chosen because it can act as the foundation for more research work to take place. Moreover, it provides a multi-dimensional approach to view information. However, it also develops a framework that can be applied to many different academic fields that involve unstructured user-generated content (i.e., online reviews) and categorized information (i.e., quality assessment scale responses).

The theoretical background helps deepen the understanding of service quality and eWOM. The Thesis theoretical basis evolves to theories that explain how people perceive satisfaction, which leads to related theories that explain what service quality is and why people might choose to share and spread their experience about the quality of a service they received to others through (e)WOM. This leads to comprehending the need to disseminate information and how people perceive this information and, finally, how more impactful online reviews can be achieved. This thesis contribution is related prominently with Information-Confirmation theory, since it attempts to provide the research community and professionals with more elaborated and multifaceted reviews. eWOM draws its theoretical base from different disciplines, including sociology, marketing, consumer behaviour and information systems (Mishra and Satish, 2016).

In the next Sections, the study first explores the theory behind eWOM spread (Social Contagion Theory) and grow (Multistep Flow Theory). Later, the theories that are more related to the Thesis' contribution to the field are presented, which concern why people share (Social Exchange Theory) and search (Elaboration Likelihood Model) for eWOM and the theory behind eWOM information adoption by readers (Information Adoption Model). Finally, the theory related to customer satisfaction and service quality assessment is discussed (Information Adoption Theory and Means Ends Chain Theory), which in the case of accommodation service quality assessment, these terms seem to coincide.

The discussion on the theoretical background is followed by a detailed review of the influential literature. First, the section presents the concept of word of mouth and its transition to electronic word of mouth (e)WOM. WOM has traditionally been a mean of communicating information and evaluations regarding a service or a product. Positive WOM is acting in favour of the discussed service or product while negative review discourages potential clients from buying the service or product. Moreover, the buyers' decision is affected by the argumentation quality (i.e., two-sided review). The introduction of the participatory web has electronically expanded the spread and reach of WOM (Blank and Reisdorf, 2012). Therefore, it has a significant impact on consumer expectations, preferences and behaviour which expands in the field of Tourism as well. Therefore, after presenting eWOM, the section discusses eWOM in Tourism and its characteristics. Specifically, in the Hospitality field, prospective travellers face difficulty choosing accommodation since it is an intangible service that is difficult to examine beforehand. eWOM simplifies their research and aids in crosschecking the intangible factors before the visit.

Moreover, eWOM is the most reliable source of information compared to other means of suggesting a service or product (Ladhari and Michaud, 2015). Also, eWOM provides valuable information that can improve hoteliers' marketing relations and management strategies (Donovan and Rossiter, 1982; Senecal and Nantel, 2004; Buhalis and Law, 2008). Followingly, the incentives for reviewers to give evaluations are discussed, as well as how negative, and positive eWOM can affect accommodation. It is indicative of the significance of eWOM in the travel industry that a 10% improvement in reviews can increase sales by 4.4%, while a 10% increase in the variance of reviews can result in a 2.8% drop in sales (Duan, Gu and WhinstonYe, Law and Gu, 2009). For this reason, it might be important to indicate the reasons that motivate guests to leave a review. These motivations may vary considerably. Among the motivational factors, one can identify the reviewers' need to develop and maintain social connections, the pleasure of ‘surfing’ online and using the Internet’s possibilities, altruism, and solidarity, ego self-feeding, expressing overwhelming feelings (Munar and Jacobsen, 2014; Hennig-Thurau et al., 2004). In the next part of the specific Section, the role of ratings in eWOM is discussed. Ratings usually involve a star rating system used to evaluate specific elements or the all-around experience of the services provided and accommodation. In contrast, review is the personal assessment in the visitor’s own words of their experience during their stay. Ratings express a sentiment of positiveness or negativeness of the review in a way similar to the Likert scale employed in service quality assessment questionnaires to express the negative or positive experience related to a question or statement.

Next, the service quality is discussed, and several service quality scales are presented. The most dominant service quality scale has been Parasuraman, Zeithaml and Berry (1988) which is based on the service quality gap. According to the authors, the service quality gap is the difference between a customer’s expectations before receiving a service and their perceptions after the service took place.

Based on SERVQUAL, many more scales have been developed and used in a variety of fields. The HOLSERV scale is one of these scales, and it is specifically targeted towards the accommodation sector (Mei, Dean and White, 1999). HOLSERV plus (Boon, Bonera and Bigi, 2013), which has been based on the HOLSERV dimensions, provide an instrument that can be used to analyze comments mined from online sources (eg. TripAdvisor). Reviews are analyzed through word frequency, and the results are assigned to the service quality dimensions of the room, facilities, surroundings, employees, and reliability.

Next the thesis provides an overview of eWOM analysis approaches based on both the intended outcome (theme of research) and methods used to analyze the information. The section explains that machine learning, each methodology may be employed in different contexts, and provides an overview of both supervised and unsupervised machine learning approaches, which lead to the selection of the deep neural network classification model that is used for the analysis of this thesis proposed multi-dimension model.

The final section of the Chapter discusses the research gap that emerges from the literature review study. The research gap has already been presented epigrammatically in Chapter one.

In the second Chapter, the gap analysis goes into more detail, and as the research gap is revealed, the derived research questions are also presented.

## 2.2 METHODOLOGY FOR THE LITERATURE REVIEW

For this research, a thorough and continuous narrative review is conducted. During the first stage, a list of keywords was determined to provide a broad spectrum of literature covering the research questions. A few trial searches were performed to customise further the keyword list based on the keywords of relevant articles. The search engine Scopus was used for the trials as it provides a great variety of quality results, which can be further customised. During this process, an essential query algorithm was optimised to provide the precise results needed. Although this study's scope is related solely to service quality and eWOM, the query covered other topics which could provide additional information or insight into service quality (i.e., delight, experience, satisfaction). During the second stage, to identify all the relevant literature, further queries based on other keywords were developed (i.e., HOLSERV, SERVQUAL, rural tourism instead of delight, experience and more) and run with Scopus and Google Scholar. Based on relevancy criteria, both the titles and all the summaries of the results were checked to discard those that were irrelevant to the search.

As the literature review progressed, additional queries were created based on new findings. For instance, in order to choose the best possible method of analyzing service quality related to hotel accommodation, a search was performed for all the different of identifying service quality methods, which includes all the applications of the SERVQUAL model as well as all the subsequent methods derived from the SERVQUAL model (i.e., SERVQUAL, HOLSERV, LODGSERV, AUTOSERV). In addition, in order to identify the various association rules methods that can be applied to Big Data instances and specifically to eWOM, further relevant queries were created to contain additional keywords such as association mining, Create Association Rule, GSP, Apriori, Eclat, FP-Growth, PrePost, and FIN.  All of the above queries were run in Scopus, taking only the peer-reviewed journals into account.

Forward searches were executed to explore additional sources and publications citing the articles selected from the keywords search. When a relevant article was discovered, all other articles of each of its authors were also reviewed, as well as all the articles quoting that specific article. Lastly, while reviewing the literature, backward searches were performed on articles and books referenced in the studied bibliography and had not appeared in the research results until that point. A review of the other work of the authors of the specific articles was also carried out. At these last stages to avoid leaving out important information, Google Scholar was also introduced, only for the cases where the articles were unavailable in Scopus peer-reviewed journals. At the end of stage 2, a full database was developed, including all search findings during the full thesis period.

Scopus and Google Scholar were chosen due to the fact that combined they seem to cover the vast majority of Journals. More specifically, according to Barnett and Lascar (2012), in a comparison between Scopus and Web of Science (Web of Knowledge), Scopus had more unique journal titles (Abrizah et al., 2013). However, both databases' unique titles had low Journal Rank Indicators (Mingers and Lipitakis 2010). Nevertheless, since there is always a possibility that important research works might be left out if one uses only Google Scholar and Scopus, a decision has been taken to include in the search all the highly ranked articles from the World of Knowledge database as well. Moreover, during the forward or backward search that a scientific journal relevant to this research is identified, a thorough search using all the keywords is performed.

The database consists of 1,638 different academic articles and books from, 184 of which are referred to in this study. From the 273 References used in this work, 15 refer to National and International Databases and International Conferences and 10 to Springer, SAGE and Routledge published books. Of the 247 remaining articles and books, 24 have been identified through the research that took place in Google Scholar to give a complete overview of the literature. The remaining 223 references come from peer-reviewed Journals acquired through the Scopus database. From these 223 Journals, 208 belong to the upper 25% of the highest-rated Journals based on Scopus's CiteScore algorithm. CiteScore is considered to be a free and more transparent alternative to Journal Impact Factor (Teixeira da Silva and Memon, 2017) and it seems to give a more realistic quartile distribution that the Journal Impact Factor distribution (Fernandez-Llimos, 2018).

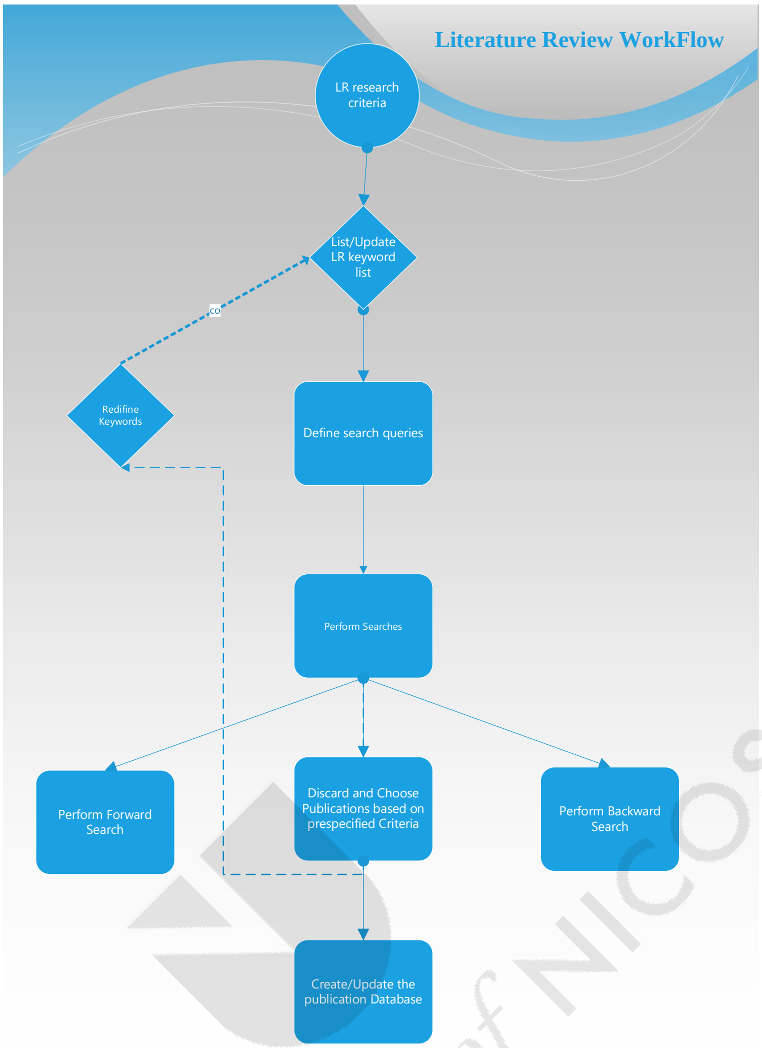



**FIGURE 1 LITERATURE REVIEW WORKFLOW**

## 2.3 AN EXPLORATORY STUDY OF THE FIELD

The following preliminary study took place during the first months of this research. Its purpose was to expand the researcher's view and perceptions so that a more comprehensive picture of the field of tourism in general and locally (in Crete) was achieved. There are a few weaknesses with this preliminary work; for instance, the mini-interviews that took place during this process were not properly scientifically designed, but nevertheless, they provided this preliminary work with information that in that infant stage guided the next steps of the process. For this work, the following persons and organizations were contacted:

- The President of the Association of Tourist Agents of Crete and Santorini
- The three primary Travel Agents of Crete (Papakaliati, Dimou (TUI), Cretan Holidays)

- The National Statistics Agency
- The Civil Aviation
- The Association of Greek Businesses in Tourism
- The President of the Agrotourism Association in Crete
- The Hotel Association of Heraklion
- The secretariat of one of the major Hoteliers and probably the future President of the Hoteliers Association of Crete
- The Executive Tourism Advisor of the Region of Crete
- The Archaeological Museum of Heraklion

A one-day conference was attended, organized by the Municipality of Heraklion for the Expansion of Tourism in Crete, to include the Winter Season. At the conference, the researcher also had an in-person discussion with the main speaker (researcher on 365-day tourism, from Sarajevo). In these grounds, additional discussions took place with a software developers' group from the University of Crete on technological innovations and new prospects in tourism (virtual and augmented reality, artificial intelligence, and more). The research on the literature continued in a broader area outside the research and field scope. Finally, the discussions and presentations from a few recent conferences in tourism were studied and the projects and papers of MIT and Harvard on tourism.

Tourism-related information and content was accessed and studied in the following open databases:

- sete.gr,
- insete.gr,
- statistics.gr,
- bankofgreece.gr,
- ipkinternational.com

The results of this work provided a broader view of the field. The mini-interviews offered a two-fold advantage: on the one hand, they provided a view of the needs of the people of tourism and their understanding concerning their services and the clients' expectations. On the other hand, it gave insight on the people of the tourism industry who have been reluctant to share their data or even give research questionnaires to their clients (some already used surveys they keep for themselves and some others just seemed reluctant to collaborate). The exception to this rule had been the President of Agrotourism of Crete, who was very helpful and promised to ask the members of her association to share the study's questionnaire link with their clients.

The results showed that it would be of both academic and regional interest to research the expansion in winter tourism, the development of agrotourism, as well as 4 and 5 star-hotel tourism in Crete. Nevertheless, working on the form of reviews that tourism websites like TripAdvisor offer, would benefit all the aforementioned fields. In the following lines, these ideas are explained in a few words.

1. One of the essential strategies that will concern Crete's tourism associations in the next few years is prolonging the touristic period to the winter season as well. The intention is to achieve high touristic demand for Crete during the whole year. In this context, the reviews could be mined, to study the differentiation of tourists' expectations and preferences, depending on the travelling season. The extracted results would provide a more sophisticated picture of travellers' needs and perceptions and ways for Crete's public and private sector to increase tourist demand in winter.
2. One of the new and fast-developing sectors of tourism in Crete is Agrotourism. As Agrotourism Association of Crete's president pointed out in a telephone interview (January 2017), Agrotourism is considered one of the industries that can bring substantial revenues to the island because they can offer various experiences i.e., olive, and grape harvesting, trekking and more. The president showed interest in the eWOM field and its promotion through the web. One could extract the online reviews and compare or supplement them with the results of questionnaires. This study can cluster the specific group of travellers by their unique characteristics aiding in providing a general profile to the world that can be used to attract travellers or/and expand the variety of experiences offered based on their answers and reviews.
3. According to a study of the Association of Greek Businesses of Tourism, by 2021, 4 and 5 stars hotel tourism in Crete will account for 30% of the total number of tourists per year, resulting in 60% of the total revenues from tourism. This means that 4-5-star hotel tourism will grow to the most critical revenue source of this particular sector. Consequently, the data mining of 5-star hotels and a few 4-star hotels can give insights to the specific group of consumers, resulting in a faster and successful expansion to the particular tourist group.

4. TripAdvisor is the largest travel platform and one of the most influential eWOM sources in tourism (Martin-Fuentes, 2019) with 463 million visitors each month, hosting 860 million reviews which are available in 49 markets and 28 languages (TripAdvisor, 2020; Yen, Chun and Tang, 2019). TripAdvisor is a travel website that helps customers in gathering travel information and posting reviews and opinions. The question is, do these reviews and opinions present a good picture of the quality of the experience travellers had from their visit? Can the questions/form given to reviewers to fill out, be considered suitable to extract the quality of experience the clients had? The SERVQUAL questionnaire was between 1983-1988 through Parasuraman, Zeithhalm, and Berry's systematic research.

The SERVQUAL scale returns customer's satisfaction based on five dimensions: Reliability, Assurance, Tangibles, Empathy, Responsiveness. The purpose of the research, in this case, is to extract the TripAdvisor reviews for the area of Crete and categorize them according to those five dimensions. Depending on how well the data fits those, one could suggest new ways to analyze data. A more homogeneous review from all travel providers, would mean easier access and analysis of information, and consequently, more efficient, and sophisticated analytics for everyone (researchers, travel agencies, hoteliers, travellers).

Despite the fact that all of these research possibilities seem equally exciting and challenging, the decision to work with the 4th option prevailed because it would be an excellent base to continue later with the other studies mentioned here. The reason is that creating a more reliable source of information is vital for both researchers, agents and travellers, in order for everyone to benefit in the long run.

## 2.4 Extant Theories

### Theoretical Foundations

The theoretical background helps deepen the understanding of service quality and eWOM. The theoretical basis is related to theories that explain how people perceive satisfaction, which leads to relating to theories that explain what service quality is and why people might choose to share and spread their experience about the quality of a service they received to others through (e)WOM. It aids the reader comprehend the need to disseminate information and how people (future service consumers, company and organisation managers, researchers) perceive this information and, finally, how more useful/impactful online reviews can be achieved. As it will become evident in the following, this thesis contribution bears a strong relation to Information-Confirmation theory, since it attempts to provide the research community and professionals with more elaborated and multifaceted reviews.

## eWOM

The action of spreading WOM and eWOM is usually explained through Social Contagion Theory. Social Contagion refers to behaviours that spread rapidly from one person to another, and are similar to viral eWOM situations. It is based on the idea that thoughts and moods can be spread virally in certain types of crowds. When the information has been received, the person's/group's behaviour becomes irrational, and people might act in ways they usually would not. When the particular circumstances that sparked the irrational behaviour pass, people return to their normal behaviours. The Social Contagion Theory has been applied to explain the formation and growth of Facebook online communities (Trusov et al., 2009). Trusov et al. (2009) indicate that eWOM has substantially higher diffused effects than traditional WOM practices, and the response elasticities that they produce are significantly higher as well.

The Multistep Flow Model suggests that new information is initially accessed by opinion leaders, who disseminate it to crowds (Katz and Lazarsfeld, 2017). Opinion leaders are more affected by media of higher status than from mass media and they affect people who are closer to their own personalities, social and economic status, interests, and demographics. Information based on the Multistep Flow Model can be affected and shaped by social norms and conflicting views of each community group they enter (Katz and Lazarsfeld, 2017). The opinion leadership approach has been utilised to explain eWOM message generation and identify the demographic that should be targeted to generate and spread information (Phelps et al., 2004). In the concept of two-way step flow, people who produce the information that affects groups are also being affected/influenced by others (Myers and Robertson, 1972).
Similarly, opinion leaders in eWOM are influenced by other reviewers (Sridhar and Srinivasan, 2012). People in online communities who have received more votes can be perceived as opinion leaders on specific communities. The voting system itself suggests that people have been influenced by this reviewer's decision and upvote it to suggest to others that it contains more significant/helpful information.

Social Exchange Theory helps us understand the reasons behind information-sharing. In social behaviour, there is tangible and intangible interaction between two or more parties. Each of these interactions entails risk/costs and benefits/rewards. In this social exchange, when costs exceed the rewards, this can lead to issues in the relationship (Munzel and Kunz, 2014; Chen, Chiang and Storey, 2012). When it comes to advising/reviews, the individuals who provide the information expect a reward for their actions (i.e., respect, approval). A couple of articles (Munzel and Kunz, 2014; Wasko and Faraj, 2005) utilised Social Exchange Theory to specify the types of contributors and the motives that lead to post online reviews. They found that among the reasons people choose to share their reviews is the positive effect it has on their reputation (Wasko and Faraj, 2005).

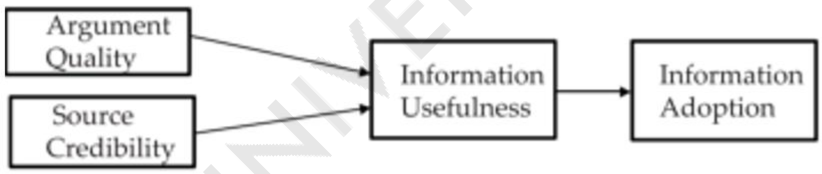
The Social Exchange Theory aids in understanding eWOM from the perspective of the reviewer. To comprehend the other side, which is the review receiver, the Elaboration Likelihood Model should be discussed first. Elaboration Likelihood Model (ELM) or Cognitive Fit Theory explains that persuasion can occur in two ways; directly or indirectly (Petty and Cacioppo, 1986). When processing information directly, people use their high-involvement route, while when they access the information pathetically, they use their peripheral route (Petty and Cacioppo, 1986). In the first case, potential customers have gone into their high-involvement mode, where they engage in the process by critically reading the reviews. The opposite happens when customers who do not have enough motivation or abilities go into their peripheral processing mode where they read online reviews and interact in a low-involvement way. In the high-involvement stage, readers are more likely to elaborate on the review, which means that the content of eWOM is more critical in this case (Park and Lee, 2008). When in the peripheral processing stage, readers having an abstract criterion that 'more is better', might accept a multi-argument message without evaluating those arguments carefully. Teng et al. (2014) examined the antecedents of the persuasive power of eWOM and concluded that one of the critical factors affecting consumer's decision is the argument quality (how convincing and persuasive is the message). The other factors are the source's credibility, attractiveness, perception and style (Teng et al., 2014).

Moreover, Filieri and McLeay (2014) came to the realization that high-involvement travellers adopt both central (quality) and peripheral (ranking) routes when they process information. They also find that travellers are more interested in finding the information they need and not complete details on each accommodation feature (Filieri and McLeay, 2014). This means that on the one hand, OTAs need to have complete information from as many reviewers as possible, so that they can provide customized information to each reviewer. To achieve this, first, the completeness of service quality arguments/dimensions shared in online reviews is discussed and whether there are dimensions that are less reviewed online.

## INFORMATION ADOPTION MODEL

Based on the theory of Elaboration Likelihood, Sussman and Siegal (2003) formulated the theory of Information Adoption Model, where the information' receiver adopts new information based on its quality and credibility. Information Adoption Model has been widely used in research in eWOM (Cheung, Lee and Rabjohn, 2008; Chen, Chen and Hsu, 2011), but also in social networks (Cheung and Lee, 2008; Zhang and Watts, 2008) and online communities (Cheung, Lee and Rabjohn, 2008; Zhang and Watts, 2008). The model goes further from the adoption of information, assuming that if people are prone to adopt information, they also tend to adopt ideas, behaviour or even technology (Sussman and Siegal, (2003). Therefore, Sussman and Siegal (2003) argue that similarly, people tend to adopt advice. This theory is closely related to eWOM, and it helps us understand how and why people engage and value online reviewing systems. As social exchange and elaboration likelihood theories show, there might be variations in the effects of a review on different people depending on the particular situations and context. However, the usefulness of a review as Information Adoption Theory points out it is also related to the source's credibility and content.

**FIGURE 2 INFORMATION ADOPTION MODEL**




**Source:** Sussman and Siegal (2003).

## SATISFACTION AND SERVICE QUALITY

Satisfaction has been the most prevalent topic of research in Tourism for a few years now (Park, 2019). Specifically, in a systematic literature review (2008-2019) Park (2019), conluces that the most researched topic in tourism is "Tourist Satisfaction" (first position in ranking) followed by Service Quality combined with different terms (3, 4, 5, 6, positions in ranking). Given its research volume, one can infer that the concepts of travellers' "Satisfaction" and Service Quality have been addressed by researchers using different theories/perspectives. The leading theory followed in both Satisfaction and Service Quality is Expectation-Confirmation Theory. Other approaches include the method of expectations/uncertainty, the equity point of view, the norm, and the overall return of the market/business (Yoon and Uysal, 2005).

From an administrative point of view, the phenomenon can be studied through its individual aspects. For example, (Kotler et al., 2017) have argued that the hotel product consists of many different layers: the primary layer is considered to be the main product (e.g., the hotel room), which is the product the customer enjoys with the purchase transaction; the next layer are the necessary conditions (e.g., a customer reception desk) that provide access to the main product, as well as all other products and services that may accompany it.

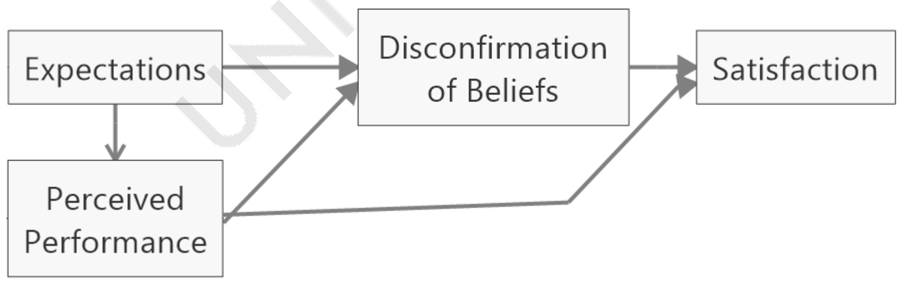
The hotel product can also be presented as a set of features that include services, geographic location, room, price/value, hygiene, food and beverages, image, marketing, and security (Dolnicar, 2003; Qu, Ryan and Chu, 2000). For example, the Two Factor Theory argues that hygiene (such as cleanliness and maintenance) does not positively contribute to satisfaction, although hygiene discomfort is negatively perceived (Noe and Uysal, 1997). At the same time, motivating factors such as the "experience" of staying in a hotel, play a decisive role in customer satisfaction (Noe and Uysal, 1997). Moreover, the 'quest' for authentic experience and service quality have been related to cultural heritage tourism and slow tourism as of late (Shang, Qiao and Chen, 2020; Nguyen PB Chau, 2020; Sam and Crotts, 2019).

The logic of Service Dominance has also been adopted recently. It states that the guest's experience is not limited to what the hotel has to offer, but is co-created by the hotel's services and the guest himself (Chathoth et al., 2013). For this reason, the satisfaction of the guest can be considered to be their assessment of the experience, together with their interaction with the various services in the area. Given the complexity of the guests' experience, measuring, and managing customer satisfaction is a pretty tricky task. In the Tourism and Hospitality industry, research has shown that there is a gap between what managers think is important for guests and what guests consider essential when choosing and assessing accommodation (Lockyer, 2005). This means that it is vital for managers to have clear and concise information on the visitors' views about the experiences they enjoyed.

According to Expectation-Confirmation Theory, Consumer Satisfaction is achieved by comparing the results of the gain of a service with the ex-ante expectation for the specific service (Thong, Hong and Tam, 2006). In other words, Expectation Confirmation Theory (ECT), indicates that post-purchase satisfaction is the pre-purchase expectation for the product/service in relation to the perceived performance (Parasuraman, Zeithaml and Malhotra, 2005; Oliver, 1977). In other words, consumer service quality and satisfaction are achieved by comparing the results of the gain of service with the ex-ante expectation for the specific service (Thong, Hong and Tam, 2006). When the product or service outperforms expectations, the resulting feeling is satisfaction. This effect is verified through positive or negative feelings. So, when the given service/product quality matches or outperforms the customer's expectations, the resulting feeling is positive.

On the contrary, when the actual performance does not meet expectations, the feeling is dissatisfaction (Oliver, 1980). The phenomenon of online reviews (ratings, content, and volume) is mainly communicated and explained through Expectation Confirmation Theory (Cheung and Lee, 2012; Hennig-Thurau et al., 2004). Purchasing decisions and behaviours are intercorrelated with the satisfactory assessment of the overall experience related to the product or service (Oliver, 1980)). The following Figure presents the theoretical model of Expectation Confirmation Theory

**FIGURE 3 EXPECTATION CONFIRMATION THEORY MODEL**




Source: Oliver (1980) as also seen in Cheung and Lee (2012)

The Means Ends Chain Theory has been utilised in research to explain consumer behaviour's motivational basis (Kaciak, 2007). According to Means-End Chain theory, consumers retain in mind abstract information about the different attributes of a product or service (Parasuraman, Zeithaml and Malhotra, 2005). Based on this information, they can later evaluate their experiences into very concrete attributes that can be synthesized into a set of groups/dimensions (Zeithaml, 1988; Parasuraman, Zeithaml and Malhotra, 2005; Parasuraman, Zeithaml and Berry, 1985). Based on these dimensions, service quality can later be associated with customer satisfaction, and WOM behaviours (Parasuraman, Zeithaml and Malhotra, 2005).

SERVQUAL, and consequently, all variations that came after, are based on the Means Ends Chain theory combined with the Expectations Confirmation Theory (Parasuraman, Zeithaml and Berry, 1988; Buttle, 1996). Parasuraman, Zeithaml and Berry (1985) identified the criteria utilised by consumers to assess service quality in 10 dimensions, which later were limited to 5: Reliability, Responsiveness, Assurance, Empathy and Tangibles (Parasuraman, Zeithaml and Berry, 1994).

It is evident that, especially when it comes to the specific field of accommodation's service quality, customer satisfaction is closely related to service quality if not synonymous. This is because satisfaction, in this case, is the result of the accommodation's product, entailing tangible and intangible parameters. As presented below, these parameters are taken into account when also assessing service quality(Parasuraman, Zeithaml and Berry, 1988).

## 2.5 Literature Review on eWOM, Service Quality and Machine Learning

### From word of mouth to electronic word of mouth

Word of Mouth (WOM) has been used as a supplementary means to traditional ways of communicating information (print media, television, radio, and more) and evaluations concerning a service or product, guiding and/or directing others in their personal choices (Litvin, Goldsmith and Pan, 2008). Specifically, according to Anderson (1998), through WOM, a customer can express one's positive or negative feelings or views regarding a specific service, product or company. Positive WOM increases the possibility of choosing the communicated idea (i.e., purchase the reviewed service) while negative WOM has the opposite effect (Ladhari and Michaud, 2015). The number of people discussing/reviewing a product might vary based on many circumstances. Engel, Kegerreis and Blackwell (1969) discovered that 90 % of buyers talked about a new product they bought to at least one person, and 40 % provided an oral review of the product to 2 or more persons. Additionally, in his research of WOM diffused for a new product, Arndt (1967) found that from the people that received a favourable review, 54 % bought the product, in contrast to only 18 % of the people that received an unfavourable product review. More recently, Cheung and Thadani (2012) explained that the credibility of a review is connected to the argument quality, the source and the review's consistency, and the admission of both positive and negative elements (two-sided review) (Cheung and Thadani, 2012).

Participatory web achieved through Web 2.0 (Blank and Reisdorf, 2012) and its rapid expansion, introduce new opportunities for user-generated content (UGC) to be created and shared (Sigala, 2011). Any user around the globe, even without technical skills, can create and publish online content for public view, creating situations of electronic word of mouth (eWOM). eWOM is different from WOM in regards to accessibility, scope (one to one, one to many, many to many), level of interactivity (synchronous, asynchronous) and speed of interaction (Luo and Zhong, 2015; Serra Cantallops and Salvi, 2014; Sun et al., 2006). Moreover, compared to WOM, which occurs between acquaintances (i.e., friends and family), eWOM is communicated in many instances from unknown sources (Xie et al., 2011). Online UGC offers the possibility for eWOM to be disseminated in various ways (Ye et al., 2011). Combining the information provided by Wensi (2017) and Cheung and Lee (2012), it is made clear that eWOM channels take the form of blogs, newsgroups, review websites, chat rooms, instant messaging and e-mails, while reviews are posted on Consumer-opinion portals (COPs) through weblogs, discussion forums, social networks or other websites. COPs are considered the most popular way of communicating eWOM in the hotel sector (Ventura, 2017). Through COPs, consumers can primarily communicate their experiences concerning any products or services, while other potential customers can read these reviews and form their decisions.

Consequently, eWOM is the communication of WOM via Web 2.0 (Hennig-Thurau et al., 2004), or as Litvin, Goldsmith and Pan (2008) suggest based on (Westbrook, 1987), eWOM represents "all informal communications directed at consumers through Internet-based technology related to the usage or characteristics of particular goods and services, or their sellers" (p.461). At the same time, it includes "any positive or negative statement made by former, actual, or potential customers about a product, service or company, which is made available via the Internet" (Hennig-Thurau et al., 2004). eWOM has an essential impact on expectations, preferences and consumer behaviour and also influences their evaluations (Luo and Zhong, 2015; Litvin, Goldsmith and Pan, 2008).

## eWOM in Tourism. Importance and characteristics of eWOM

Despite what was mentioned previously, in the accommodation sector, travellers rely on both WOM and eWOM (Bronner and Hoog, 2011). WOM at first (Butler, 1980; Cohen, 1988; Morgan, Pritchard and Piggott, 2003), and now eWOM as well (Serra Cantallops and Salvi, 2014; Ong, 2012) have been playing an essential role in travellers' decision making. Prospective travellers are always seeking additional information that can simplify their research and aid in crosschecking the quality of intangible factors (i.e., the quality of service provided or bed's comfort) that affect their travel decisions (Litvin, Goldsmith and Pan, 2008). Öğüt and Onur Taş (2012) claim that eWOM's impact might be more significant than WOM's, because the former not only dynamically has a vast number of recipients but it is also not constrained by distance and time (Duan, Gu and Whinston, 2008; Bhatnagar and Ghose, 2004). Compared to information provided by travel service providers, readers often perceive reviews posted by fellow travellers to be more up to date, amusing and reliable (Gretzel and Yoo, 2008). In the case of tourism, prospective travellers can virtually live situations through the stories left in user-generated content by other travellers (Chen and Law, 2016). Serra Cantallops and Salvi (2014) note that eWOM has affected the hotel sector the most within the tourism industry. Moreover, independent travellers are found to progressively rely more on online reviews (Jeacle and Carter, 2011; Ye et al., 2011), while also travellers in general taken eWOM into serious consideration while researching for accommodation for their trips (Cheng and Zhou, 2010; Tian, 2013). Specifically, during their research for reservations, 84 % of the travellers were influenced by the reviews they read (Milan, 2007).

EWOM has become a significant source of information due to its enhanced volume, dispersion, persistence and observability, anonymity and deception, the salience of valence, and community engagement (King, Racherla and Bush, 2014). The importance of eWOM has been repeatedly verified (Klaus and Changchit, 2017; Clare et al., 2016; Sparks and Browning, 2011). Klaus and Changchit (2017) found that prospective travellers perceive online reviews as easy to access, credible and useful and tend to consult them before making decisions. Based on recent studies, travellers are likely to change their booking decisions based on the online reviews they read (Sharifi, 2019; Ramanathan, Subramanian and Parrott, 2017). So, if the reviews tend to be positive, the reviewer will tend to trust the hotel and book there and vice versa (Sparks and Browning, 2011).

EWOM, when compared to other means of recommending a product or service such as print ads, personal selling, and radio and TV advertising, has been found to be a more reliable ways of exchanging information (Ladhari and Michaud, 2015). Offline channels have been found to reach up to twice as few customers in comparison to those reached by websites that offer reviews (Hamdi, 2017). This is possibly due to the fact that COPs are available to anyone with internet access while WOM information can only reach close friends and families (Romaniuk, 2016). Nowadays, the vast majority of consumers (77.9%) are likely to check online hotel reviews before making their travel decisions (Mishra, 2016). According to (Chong et al., 2018), eWOM plays a twofold role in travellers' decisions since it informs and recommends accommodation and services (Park and Lee, 2008). On the other hand, eWOM provides valuable information that can improve hoteliers' management (Donovan and Rossiter, 1982; Senecal and Nantel, 2004) and marketing relations, aiding them to create more client-centric strategies (Buhalis and Law, 2008). Owing to all the reasons mentioned above and its characteristics, e-WOM has been receiving the academic community's continuous attention, whether it is in marketing, e-commerce or e-tourism field (Filieri and McLeay, 2014).

### Negative - Positive eWOM. Incentives to give evaluations

Both WOM and eWOM have been widely analyzed in research studies. It has been found that positive eWOM generates positive attitudes and increases sales opportunities, while negative eWOM generates the opposite effect (Thong, Hong and Tam, 2006; Karakaya and Barnes, 2010; Lee, Park and Han, 2008; Steffes and Burgee, 2009), especially in the hospitality sector (Pantelidis, 2010; Vermeulen and Seegers, 2009; Ye, Law and Gu, 2009). Duan, Gu and WhinstonYe, Law and Gu (2009) suggest that a 10% improvement in reviews can increase sales by 4.4%, while a 10% increase in the variance of reviews can result in a 2.8% drop in sales. Moreover, Hennig-Thurau et al. (2004) explain that especially for displeased customers, online platforms make it easier to reach the companies and inform thousands of prospective customers as well. EWOM, can also positively affect the travel intention, tourist attitude and destination image (Jalilvand and Samiei, 2012; Reza Jalilvand and Samiei, 2012). As already mentioned, if a hotel's reviews are predominately negative, the reviewer will tend not to trust the hotel, while if the reviews are mainly positive, the travellers tend to book there (Sparks and Browning, 2011). Supporting this statement, El-Said (2020) indicates that although reviews with positive valence might not impact bookings, reviews with negative valence have a significant impact on booking intention. Moreover, negative reviews can outweigh a good friend's positive recommendation (Arvemo, 2019).

Consequently, hoteliers need to comprehend which types of hotel experiences motivate tourists to post online reviews (Harrison-Walker, 2001). Understanding the incentives for reviews can help marketers know how to improve their services and encourage positive e-WOM (Jeong and Jang, 2011). These motivations to evaluate a hotel may vary considerably. Reviewers might be motivated by the need to develop and maintain social connections, the pleasure of 'surfing' online and using the Internet's possibilities, altruism, and solidarity, ego self-feeding, expressing overwhelming feelings (Munar and Jacobsen, 2014; Hennig-Thurau et al., 2004). For example, visitors can evaluate accommodation just for the pleasure of voicing their satisfaction or to exert their anger and indignation (Hennig-Thurau et al., 2004). Thus, while some might be interested in improving service quality, others may simply show contempt (Oliver and Swan, 1989; Gretzel, 2007; Gretzel and Yoo, 2008). Also, travellers often value the hotel's services from altruistic interest for the next traveller (Munar and Jacobsen, 2014; Hennig-Thurau et al., 2004), or with the intention to help the hoteliers. In general, users try to recommend good hotels and warn about those below their expectations (Gretzel and Yoo, 2008).

### RATINGS' ROLE IN EWOM

Generally, eWOM can be broken down in ratings and reviews. Ratings are usually a star rating system used to evaluate specific elements or the all-around experience of the services provided and accommodation. In contrast, review is the personal assessment in the visitor's own words of the experience they had during their stay. Specifically, customer ratings are considered today to be one of the most critical types of consumer-generated information that can lead to an understanding of customer behaviour and, hence, enhance business performance in hospitality and tourism (Serra Cantallops and Salvi, 2014; Browning, So and Sparks, 2013; Mauri and Minazzi, 2013). At the same time, research results confirm that a hotel rating is the most reliable predictor of a customer's experience (Schuckert, Liu and Law, 2015; Gu and Ye, 2014; Yacouel and Fleischer, 2012). Online hotel ratings are considered more objective, immediate and without sample bias, as they are created spontaneously and without any laboratory treatment that takes place when working with service quality assessment scales (Schuckert, Liu and Law, 2015). According to Gu, Park and Konana (2012), an increase in the positive ratings can substantially increase bookings and, consequently, the hotel's revenues. On the other hand, negative ratings and online complaints can negatively affect bookings and revenues, and it is vital when they occur that they be contained and localized while dealt in a professional manner (Buhalis and Law, 2008).

Many customers consult with this online information when planning their travel, so previous guests' evaluations can drastically affect their final travel arrangements, expectations, and behaviour, before and during their journey (Min, Lim and Magnini, 2015; Gretzel and Yoo, 2008). In conclusion, ratings and reviews need to provide multi-dimensional information so that each involved party gets a complete overview of what they seek.

## RESEARCH ON REVIEWS AND SATISFACTION

Recently, researchers have made an effort to study the phenomenon of Travellers' Satisfaction through the reviews given regarding the accommodation they have visited.

Stringam and Gerdes (2010) analyze customer reviews from hotel rental websites to locate repetitive words and phrases and how they relate to hotel characteristics. Furthermore (Padma and Ahn, 2020) identify interaction with employees and room quality as the main drivers of customers' reviews for 4-5 star hotels. Alrawadieh and Law (2019) suggest that service quality, rooms' quality and size are mainly determined by guest satisfaction. Similar research (Chaves, Gomes and Pedron, 2012) has found that the most commonly used words in the ratings of Portugal's small and medium hotels are room, location, cleanliness, friendliness, and service. By studying the ratings of two- and four-stars hotels, Rhee and Yang (2015) categorized the importance of these factors in relation to the category of accommodation.

Zhou et al. (2014) studied user reviews from the website Agoda.com for prominent hotels in Hangzhou, China, in order to identify the main factors influencing customer satisfaction in hotels, and managed to identify 17 different factors. Based on the influence that these factors can have on the reader, the authors categorized them as positive, negative, and neutral.

Of course, customer satisfaction factors can affect readers in various ways, depending on the personality types (Özge Kocabulut and Tahir Albayrak, 2019). For instance, depending on the type of travellers (solo, business, family, friends), one can expect to have different preferences and satisfaction criteria (Le Wang et al., 2020). Also, one can expect that visitors from a particular cultural environment (e.g., speaking a specific language) will have different accommodation preferences and expectations than visitors from another cultural environment (Dolnicar, Grün and Gru, 2007). Based on this, Tse and Ho (2009) studied the quality of services provided to customers from different cultures. They concluded that clients having different cultural backgrounds can evaluate differently the services and the products that they are being offered. Studying the cultural differences presented by Hofstede concerning online reviews, Litvin (2019) concludes that travellers should also be marketed based on their origin. Ounsri (2019) studied the perceptions of service quality using SERVQUAL, based on the travellers' place of origin, and found that cultural differences affect travellers' satisfaction criteria.

Similarly, recent studies show that Hofstede's cultural dimensions (power distance, individualism, uncertainty avoidance, masculinity) have a predominantly negative influence on online hotel ratings (M. Mariani (2019) as well as on customer satisfaction (Sam and Crotts, 2019), that is, the higher the cultural dimensions, the lower the hotel ratings. Studying the differences between travellers of Asian and Western descent in hotel accommodation in Singapore, Mattila (1999) found that Western travellers gave higher ratings to hotel services than Asian travellers. However, Mattila did not arrive at similar results when comparing Western and Asian travellers on a business trip.

## SERVICE QUALITY (FROM SERVEQUAL TO HOLSERV+)

Service Quality has been of interest to researchers and hoteliers since it is directly linked to customer satisfaction (Chen and Chang, 2005) and WOM, and indirectly to customer decision and loyalty (Sureshchandar, Rajendran and Anantharaman, 2002). Service Quality is also known to contribute to market share and profitability (Valarie A. Zeithaml, 2000), therefore becoming an integral part of a large number of organisations today, which might create competitive advantages and affect profitability. Moreover, Service Quality is directly linked to WOM. According to Boulding et al. (1993), service quality positively affects loyalty and positive WOM. At their model of behavioural consequences of service quality, Zeithaml, Berry and Parasuraman (1996), indicated that positive behavioural intentions (including WOM) are related to service quality. Alexandris, Dimitriadis and Markata (2002) suggested that service quality explained 85 per cent of purchase intention and 93 per cent of WOM variance.

Parasuraman, Zeithaml and Berry (1988) argued that from the customers' point of view, Service Quality is the positive or negative distance from customer expectations to the actual services provided, while (Zeithaml, 1988) advocates that customers understand Service Quality as overall service superiority. Naturally, Service Quality can be broken down into a few dimensions (availability, accessibility, accommodation, affordability, acceptability) (Vandamme and Leunis, 1993).

Parasuraman, Zeithaml and Berry (1988) developed the SERVQUAL model. SERVQUAL is an instrument consisting of a 31-item scale used to measure service quality gaps. Based on their research, Service quality gap is the difference between a customer's expectations before receiving a service, and one's perceptions after the service took place (Parasuraman, Zeithaml and Berry, 1985). The main dimensions of SERVQUAL model are the following:

Tangibles: personnel appearance, physical facilities, equipment
Reliability: ability to deliver the service promised
Responsiveness: eagerness to aid customers and offer prompt service.
Assurance: knowledgable, trustworthy employees with courtesy conveying confidence
Empathy: caring and personalized attention to each customer

Later in (1988), Parasuraman, Zeithaml and Berry, based on their work from 1985, were led to modify the initial SERVQUAL model. This second model has been used extensively ever since, in its original form or customized, as a model for measuring Service Quality in various fields (i.e., tourism, museums, automobile). The instrument consists of 22 items categorized into five dimensions: tangibility, empathy, reliability, responsiveness, and assurance. The customer evaluates the Service Quality by identifying the difference between their expectations and the service provided for those dimensions (Seth, Deshmukh and Vrat, 2005). Of the five dimensions of the SERVQUAL instrument, reliability is the only one related to the delivered service result and whether it was as promised. The remaining dimensions are related to the process of the delivered service.

SERVQUAL has also attracted criticism due to its broad applicability in research (Buttle, 1998; Cronin and Taylor, 1992). Cronin and Taylor (1992) argue that SERVQUAL is based on a satisfaction paradigm rather than a behavioural model. In their research, they applied their model (SERVPERF) and SERVQUAL in four industries (banking, fast food and dry cleaning) and concluded that SERVQUAL was a good fit in only 50% of the cases (banking and fast food). Despite the criticism, there have been a few successful applications of the SERVQUAL model for hotels, although further customization was usually desirable (Saleh and Ryan, 1991). Buttle (1996), argues in favor of the model's validity and stability and from one context to the other and about the number of dimensions. Nonetheless, Parasuraman, Zeithaml and Berry (1988, 1994) refer to their model as generic, and as seen from different studies, the dimensions should be, and they are actually customized, according to the context and industry (Akbaba, 2006; Getty and Thompson, 1994; Hansen, 2014; Knutson et al., 1990).

As mentioned above, service quality has been attracting the interest of researchers for a few years now, resulting in a large number of models and measurement methods (Seth, Deshmukh and Vrat, 2005). A few researchers adapted and customized their own measurement scales to the SERVQUAL model generating new models.

Among those models, one can find HOLSERV (Mei, Dean and White, 1999) and HOTELQUAL for Hotels, LODGSERV for the accommodation sector (Knutson et al., 1990), LODGQUAL for the lodging industry (Knutson et al., 1990), DINESERV for restaurants (Stevens, Knutson and Patton, 1995), HISTOQUAL for historical places (Frochot and Hughes, 2000), ECOSERV for ecotourism (Khan, 2003), RURALQUAL for rural accommodation (Loureiro and Miranda G., 2009) and AUTOQUAL for the car sales industry (Gencer and Akkucuk, 2017).

Based on the SERVQUAL model, Akbaba (2006) constructed a model that also has five dimensions, but with a different structure. Akbaba's new scale's application is more straightforward since the new dimensions are more distinct. Mei, Dean and White (1999) also customized SERVQUAL by adding two more dimensions (employees and reliability) and enriching the tangibility dimension.

Mei, Dean and White (1999) created the HOLSERV model during their research in the hospitality industry. They distributed 1,000 questionnaires at five mid-luxury hotels in Australia and received 155 responses. They examined the service quality dimensions and extended the SERVQUAL scale by including eight new items primarily related to the hospitality industry. Among their key findings was that Service Quality is represented by three dimensions: "employees" (behaviour and appearance), "tangibles" and "reliability".

Additionally, they indicated that the overall service quality is best predicted by the "employees" dimension.

HOTELQUAL was developed by Delgado et al. (1999), specifically for the Spanish lodging services. Their adaptation started from the SERVQUAL scale and its five dimensions and was applied in Madrid's customers and hotels. They resulted in three similar dimensions: the evaluation of service personnel, the evaluation of the facilities and service organisation, which they found to have high reliability and validity levels.

LODGSERV was designed for the hotel lodging industry to measure consumers' service quality expectations, and it consists of a 26-item index (Knutson et al., 1990). Knutson et al. (1990) created their adaptation based on the 31-item SERVQUAL scale and reconfirmed the five dimensions of Tangibility, Reliability, Responsiveness, Empathy, and Assurance were initially proposed by Parasuraman, Zeithaml and Berry (1985). The initial LODGSERV model consisted of 36 items designed to capture different aspects of the five aforementioned dimensions. After several stages, they resulted in the 26-item scale of LODGSERV since 10 of the original 36 questions did not contribute meaninfully to the scale.

LODGQUAL was also developed for the lodging industry (Getty and Thompson, 1994) to provide a reliable and valid scale of measuring customers' perceptions concerning the delivered quality. Parasuraman, Zeithaml and Berry's (1988) SERVQUAL model provided the basic structure used to create LODGQUAL. They emphasized separating tangible from intangible dimensions to make it easier for managers to have a clear understanding and create more effective strategies.

LQI was created by Getty and Getty(2003). It was also based on the SERVQUAL model applied by Parasuraman, Zeithaml and Berry (1988), the process of which was initially theoretically outlined by Churchill (1979), and also on the procedure for developing quality scales presented by Getty and Thompson in (1994), during their work on LODGQUAL model. This model was also designed for hospitality managers to be able to create effective strategies based on services delivered. They ended up in a model capturing the lodging industry's dimensions, which were different from the initial five dimensions of Parasuraman, Zeithaml and Berry (1988). The new dimensions are tangibility, responsiveness, reliability, confidence, and communication.

E-S-QUAL was developed by Parasuraman, Zeithaml and Malhotra (2005) to assess electronic service quality. Together with E-S-QUAL they created E-RecS-QUAL, which is intented for online customers that do not have frequent encounters with the web sites. The first scale contains 22-items and the second 11-items. The dimensions used for the first scale are efficiency, fulfilment, system availability, and privacy and for the second, responsivenss, compensation and contact. What is interesting in this case is that the creators of the initial SERVQUAL scale decided to add dimensions related to "value" in their new scales. Value is a parameter of dimensions that have not been included in any other service quality assessment scales.

RuralQual was developed in 2009 by Loureiro and Miranda for measuring service quality of the rural industry services provided in two regions, Extremadura in Spain and Alentejo in Portugal. They used factorial analysis to specify the appropriate service quality dimensions for the lodging industry. The resulting RURALQUAL instrument was also based on the SERVQUAL scale, and comprised of five dimensions: Professionalism, Tangibility, Basic and Complementary offer, Rural, and Regional Environment. In their results, these dimensions explain 78.6% of the variance in client satisfaction. They indicated the hygiene and clean look of employees, surroundings, and rooms, as the most decisive parameters.

Akbaba (2006) customized the SERVQUAL model so that it can be applied in the business hotel sector in an international environment. By studying the expectations of business hotel customers, Akbaba (2006) intended to provide business hotel managers with an instrument that would help them make more efficient decisions concerning customers. Although the five dimensions of SERVQUAL proved valid through this study, the findings indicated some components that were different from the SERVQUAL's ones. In this case, the five dimensions were adequacy in service supply, tangibles, assurance, convenience, understanding, and caring. In this study, Business Travellers found the dimensions of convenience, assurance, tangibles, adequacy in service supply and understanding and caring, to be most important in an ascending order.

HOTSPERF (Tefera and Govender, 2016) was developed by combining SERVQUAL with SERVPERF instruments, in order to study the hotel sector of a developing country like Ethiopia, at the time of the study. It was validated in a survey of 1200 guests to Ethiopian hotels. They resulted in a 25-item scale, named HOTSPERF, with two dimensions, tangibles, and intangibles.

Albacete-Saez, Mar Fuentes-Fuentes and Javier Llorens-Montes (2007) extended the SERVQUAL model to create instruments specifically for managers of rural tourism lodgings. They ended up with five dimensions: tangible elements, complementary offer, tourist relations, personnel response, and empathy. (Albacete-Saez, Mar Fuentes-Fuentes and Javier Llorens-Montes, 2007).

Saravanan (2019), based on SERVQUAL, developed a service quality scale for budget category hotels. The scale has five dimensions, namely reliability, assurance, responsiveness, empathy and technology. Saravanan (2019) suggested that SERVQUAL is still a valid and reliable scale to use as a service quality measurement tool.

Thi and Thuy (2019) extended SERVQUAL and ECOSERV (derived from SERVQUAL as well) into the Tetraclass model. With this model, Thi and Thuy (2019) postulate 47 ecotourism service quality attributes related to ecotourism, grouped into ten dimensions and four categories (Basic, Key, Plus and Secondary).

The models mentioned above have been used to study service quality through questionnaires, so they are more relevant to WOM. When it comes to online comments, it is difficult to categorize them into SERVQUAL dimensions (Xiang and Tussyadiah, 2014) as the model was created to group service quality into dimensions based on prespecified questions. This made it difficult for researchers to come to a common understanding of how the comments' elements should be grouped, except for the tangibility dimension, which was easy to identify. On the other hand, HOLSERV was found to be a better tool for working with online reviews, as its dimensions are a lot more distinctive than others'. In HOLSERV, the tangibility dimension is apparent and provides some specific definitions for the employees and reliability dimensions. Moreover, Xiang and Tussyadiah (2014) categorized online reviews by adapting the tangibility dimension of HOLSERV into a tool (HOLSERV+) compatible with text-based information. When working in both online and offline material, working on these two tools can ensure homogeneity and comparable results. The HOLSERV plus method was proposed by Boon, Bonera and Bigi(2013) to provide an instrument that can be used to analyze comments mined from online sources (eg. TripAdvisor). The reviews are analyzed through word frequency and the results are assigned to the service quality dimensions of room, facilities, surroundings, employees, and reliability. These dimensions are based on the ones initially proposed by Mei, Dean and White (1999), customized however to distinguish among different tangibles for the hospitality sector.

## MACHINE LEARNING IN EWOM

This section offers an overview of eWOM analysis approaches based on both the intended outcome (theme of research) and methods used to analyze the information. In machine learning, a methodology may be employed in different contexts; moreover, multiple methodologies may be applied in a complementary way to serve better a research goal (Stivaktakis and Kokkinaki, 2020)

EWOM communication is mainly found in various portals, online shops, music, video streaming web sites, virtual reality, online video games, travel portals, forums, and social networks (Schmäh, Wilke and Rossmann, 2017). Within this context, Jansen et al. (2009) study eWOM on Twitter in relation to brands. Amblee and Bui (2011) study the effect of eWOM on a closed community of book readers (Amazon Shorts e-books), using regression analysis, and find that eWOM can help in conveying the reputation of a product, brand, and complementary goods (Amblee and Bui, 2011). Chen, Chen and Hsu (2011) use negative binomial regression with automobile-model data from various online consumer review sources to study the effect of consumer posting behaviour with marketing variables such as product price and quality.

Processing of electronic word of mouth can be examined with regards to descriptive or predictive methodological approaches. Descriptive methods involve Summarization, Clustering or Association Rules, whereas predictive methodologies, on the other hand, involve Classification and Regression (Stivaktakis and Kokkinaki, 2020). eWOM can also be classified, based on the learning technique employed, namely Supervised or Unsupervised Learning. Usually, Supervised Learning is used for classification and regression purposes. Supervised Learning techniques include Naïve Bayes models and Support Vector Machine, Binominal Regression. An example would be the work of Ye et al. (2011) who used a log-linear regression model to study the effects that online reviews have on hotel bookings. Their analysis revealed that user-generated content has a significant impact on bookings and sales. Also, Chintagunta, Gopinath and Venkataraman (2009) use regression analysis to estimate generalized methods of moments (GMM). In their research, they study the geographical area of movie box office sales data in relation to responsiveness to advertisement and eWOM

(Chintagunta, Gopinath and Venkataraman, 2009). In the same wavelength, the studies by Jansen et al. (2009) and Salehan and Kim (2016) also use sentiment analysis on eWOMs.

Unsupervised Learning is usually applied when clustering or tasks related to association rules are sought to be addressed (Stivaktakis and Kokkinaki, 2020; Schmäh, Wilke and Rossmann, 2017). Many times, unsupervised models use k-memoids algorithm, expectation-maximization, unlabelled samples, Rule Mining, Market Basket Analysis, Collaborative Filtering, Link Analysis, and others. Sentiment analysis can be employed with unsupervised, supervised or even semi-supervised models (Stivaktakis and Kokkinaki, 2020). For instance, Hennig-Thurau, Wiertz and Feldhaus (2015) proposed a novel multi-text summarization technique for hotel reviews using k-memoids algorithm.

The process of extracting meaningful analytics from eWOM requires the transformation of downloaded data into clean data units or features to be easily processed. Depending on the researcher's ultimate goal, features can range from textual data: from documents down to sentences, words, or characters. This process is usually called tokenization, and the distinct units of text are called types. The types of counts' can be encoded and collected in vectors (Wiedemann, 2016). The process from the extraction of data to the final point of getting meaningful results consists of many steps based mainly on the goals and nature of data. For example, Guo, Barnes and Jia (2017) during the text pre-processing phase, eliminated non-English characters and words, used word text tokenization, part-of-speech tagging, replaced common negative words, stemming, and removed low-frequency words, using Natural Language Toolkit (www.nltk.org) in Python. Hennig-Thurau, Wiertz and Feldhaus (2015) proposed a summarization technique at their suggested pre-processing tasks, including part-of-speech tagging, stop word elimination, POS filtering, and sentence selection, which results in sentences with at least one noun and one adjective. For their study, they utilise the Stanford Loglinear POS Tagger software (Hennig-Thurau, Wiertz and Feldhaus, 2015).

### UNSUPERVISED METHODS

Unsupervised methods support inductive approaches of analysis because they help explore structures in vast amounts of unknown data, whereas supervised analysis supports deductive approaches since they utilise external theory-driven knowledge. Unsupervised learning algorithms are used to uncover previously unknown patterns and structures from data. They are used when we have no idea what the output values might be, so no other techniques like regression or classification can be applied. Unsupervised learning data-driven approaches return data in clusters that satisfy specific similarity criteria. Applications of unsupervised learning techniques include clustering, anomaly detection, association mining, and latent variable models. Unsupervised applications include clustering, topic models and dimensional scaling. In machine learning, besides supervised method and unsupervised methods, there is also the option to have semi-supervised approaches utilizing techniques from the supervised/unsupervised pool of methods.

Cluster analysis is the process through which context units (i.e., sentences, phrases, words) are divided into groups (clusters) in ways that context units in each group are more similar than any other objects at the other groups. There is a variety of clustering algorithms such as hierarchical, partitioning, and fuzzy clustering methods. In some methods, the algorithm automatically identifies the number of clusters while in others, the number of clusters must be entered. Hennig-Thurau et al. (2004) proposed a multi-text summarization technique for hotel reviews using k-memoids algorithm (based on the k-means algorithm). They calculate each sentence's importance based on the author's comments, comment usefulness, comment time and comment sentence. They then evaluate the similarity between sentences based on content and sentiment similarity to result in the top-k selected sentences.

Topic models are statistical models that identify the main abstract themes (topics) present in the text (Guo et al., 2017) and discover hidden patterns in the corpus. Latent Semantic Analysis, Latent Dirichlet analysis, Probabilistic Latent Semantic Analysis are some of the modelling techniques. Topic modelling may also be applied to identify readers' interests. Topic Modeling utilizing Latent Semantic Analysis (Wiedemann, 2016) and Latent Dirichlet Allocation (Blei, Ng and Jordan, 2003) have also been applied to identify and reduce dimensionality. The underlying assumption in topic modelling is that every corpus contains various topics, and each topic is associated with a group of words. Identification of latent topics leads to diminishing dimensionality. A limitation of topic modelling practices is that they neglect the order of word occurrence in the text.

### SUPERVISED METHODS

The model can be trained in supervised learning methods based on an existing dataset that contains known values for the target variable. Consequently, the algorithm uses this prior knowledge to infer answers or predictions for the corpus that we want to research. Unlike unsupervised models, the algorithm can be trained in supervised learning and can be applied directly to problems utilizing regression or classification. Supervised learning techniques include Classification, Information Extraction and Sentiment Analysis. Ye, Zhang and Law (2009), classify eWOM polarity based on different destinations using three supervised learning methods, Naïve Bayes, SVM, and N-gram model. They conclude that SVM and N-gram produced more precise results than Naïve Bayes approach, although all methods returned at least 80% accuracy (Ye, Zhang and Law, 2009).

Classification analysis is the supervised process of assigning units to categories/classes (Stivaktakis and Kokkinaki, 2020). The goal of classification is to predict with precision the target category for each case in the data. For instance, Berezina et al. (2016) utilised PASW software capabilities to classify hotel online reviews' text in categories according to customers' positive or negative recommendations. In their study, they also used CATPC software, which produced a more detailed word categorisation. Their findings indicate that satisfied customers refer more often to intangible aspects of their hotel accommodations, whereas dissatisfied customers mention more the tangible aspects of their stay (Berezina et al., 2016).

In contrast to unsupervised clustering, where the groups are built based on the emergent structure within the data, the categories are usually based on external information from pre-trained data in supervised classification. Named entity recognition is a technique applied to identify and classify unstructured data in pre-specified categories. For instance, named entity recognition, is used to identify person names, organisations, locations, etc. Sentiment Mining or Opinion Mining is the process of identifying, extracting, and analyzing peoples' opinions from the corpus. Hearst (1992) first proposed extracting direction-based information from the text (Sharef, Zin and Nadali, 2016). Sentiment mining utilises the power of Natural Language Processing, Machine Learning, and Statistics. The method chosen is based on the available information. In many instances, the followed approach is a combination of the available methods so that a more reliable and precise result is reached. The classification can be either at the level of document or message, sentence, phrase, and word level. According to Medhat, Hassan and Korashy (2014), sentiment classification techniques may employ machine learning or Lexicon based approaches. Lexicon-based approaches may use a corpus-based or dictionary-based technique. In either case, the algorithm uses a collection of pre-specified sentiment terms. There is a third hybrid solution that utilises both dictionary and corpus techniques to analyze sentiment.

Ensemble Learning Technique is a machine learning technique that combines different algorithms to produce an optimized predictive model. It is credited with decreasing variance (through bagging), bias (through boosting) and as a result, improving predictions (through stacking). Bagging, boosting, and stacking are different types of techniques that collectively form the predictive ensemble meta-model. There can be a lot of different approaches to ensemble technique. For instance, Singh et al. (2017) use an ensemble learning technique employing multiple base learners, dividing a large data stream into small data blocks. The smaller classifiers were trained on each block individually. Next, they combine all classified results produced by the smaller classifiers to one ensemble classifier. It is reported that the smaller size of the classifiers reduced the costs and the power processing needs of the study (Singh et al., 2017).

## 2.6 Research Gap

### Online Reviews as a Quality Assessment Source

By extracting and clustering information from online reviews, researchers have been working on correlating these data with customer satisfaction and service quality provided by hotels. Specifically, Zhou et al. (2014) studied user reviews from the website Agoda.com for prominent hotels in Hangzhou, China, to recognize the main factors influencing customer satisfaction in hotels. The authors managed to identify 17 different factors and, based on their influence on the reader, categorized them as positive, negative, and neutral.

Additionally, there have been a few studies successfully pairing the extracted results from online reviews to higher level (i.e. tangibles, reliability, responsiveness, empathy) service quality dimensions (Boon, Bonera and Bigi, 2013; Li, Ye and Law, 2013; Duan et al., 2013; Palese and Usai, 2018). Although these studies have used different approaches, they have reported positive results. This statement is supported by Xiang and Gretzel (2010), who observe that hotel managers increasingly use travel review platforms for their market research strategies.  Duan et al. (2013) point out the need to understand how online reviews affect the hotels' service quality approaches and, consequently, actions taken and their strategies. Li, Ye and Law (2013) emphasize the need for researchers to study the role online reviews play within organisations as part of their service quality measurement system.

## TRADITIONAL TOOLS VERSUS ONLINE REVIEWS

Berezina et al. (2016), remarked that online reviews support the basic structure of service quality scales, which separate tangible (i.e., room furnishing) from intangible (i.e., stuff services) aspects. Based on the assumption that classical survey scales' databases fulfil all quality criteria, Gretzel et al. (2010) researched whether online reviews can provide such information. They found that although customers' reviews do not differ fundamentally from traditional surveys, they do share some differences. For instance, online reviews can be assessed in real-time (Gretzel et al., 2010), making the hotel's reputation management system more effective.

Additionally, they found that managing service quality through online reviews is a more cost-effective process than traditional surveys. Moreover, Li, Ye and Law (2013) suggest that service quality assessment tools designed specifically for online reviews, provide hotel managers with more accurate information than traditional surveys. They even mention that since customer reviews are based on open-ended questions (versus the fixed questions of quality surveys), they might provide additional service quality information that service quality assessment scales do not cover. The findings mentioned above show that there is potentially overlapping information between traditional surveys and online reviews, with the latter possibly providing more information and accuracy. So, based on hotel managers' perceptions, it is essential to understand if there is overlapping or/and unique information provided by each of these tools. On the other hand, Boon, Bonera and Bigi (2013) suggest that online reviews create an opportunity to understand how customers prioritize service quality dimensions and to cluster customers based on their geographical location, ethnicity, and more. They add that online reviews cannot replace traditional service quality tools, but hotels should combine both to understand service quality better.

Lockyer (2005) indicates a gap between managers' perceptions of what is essential for guests and what guests perceive as important when choosing accommodation. Service Quality has attracted researchers' attention, resulting in a significant number of different scales (Seth, Deshmukh and Vrat, 2005). By utilizing service quality instruments (i.e., SERVQUAL, LODGSERV, HOLSERV) managers have been successfully reducing the gap in question. Consequently, managerial promotional strategies are formed mainly by using Service Quality questionnaires that give them an overview of their customers' perceptions. Koch and Benlian (2015), however, mention that very little attention has been given to classic promotional tactics, while Berger (2014) suggests traditional promotional tactics which have been applied to the offline world can provide us with new insights regarding drivers of consumer behaviour.

Additionally, online reviews have grown exponentially during the last decade, making it difficult to process and deduct useful and quality information (Liu and Park, 2015). Review helpfulness is linked to review accuracy (Aghakhani, Kalantar and Salehan, 2016). It seems that customers value genuine online reviews as more helpful, accurate and objective (Shin, Koo and Chung, 2015; Schindler and Bickart, 2005), as opposed to ambiguous and emotional reviews (Li et al., 2011). Enhancing the argument quality Review Providers will expand the adoption of eWOM in travel planning and increase their repeat visitors (Guillory, Lohtia and Donthu, 2016). So, it is in Review Providers' hands to share more efficient Analytics by acquiring better-structured reviews. The review form currently offered to be filled out by travellers can be seen in Figure 4.

On the other hand, customers shape their overall perceptions of service quality in the areas that are most important to them (Liu and Park, 2015). Since each individual perception of importance is different, a customer will rarely give a comprehensive review that will be useful to a wide spectrum of travellers. Moreover, it can be considerably rare for a reviewer to provide information concerning all the different dimensions discussed from quality assessment questionnaires by answering an open-ended question about their experience.
This problem might be overcome with data mining and the extraction of quality assessment information from a large corpus of online reviews. From the aforementioned, the research is led to the following questions:

## RESEARCH QUESTION

**What aspects of a traditional survey are represented by eWOM?**

As shown in the previous sections, one of the vital tools in tourism consumption studies is service evaluation questionnaires. For a couple of decades, hotel managers have been collecting and analyzing information using these tools to understand how consumers perceive their services. Their information can be utilised to improve the services hoteliers offer, leading to more pleased customers and, consequently, greater profit gains.

In recent years, online platforms have been developed, offering consumers the possibility to share their experiences of hotel services with others. This is a handy tool for potential customers since it can aid in leading to better decisions. From the perspective of hoteliers, it can also be a useful tool that helps them gain insight into the hotel's service quality. Although online reviews have been introduced for a few years now, providing hotel managers with information regarding their service quality, service quality questionnaire are still widely in use (Tefera and Govender, 2016; Chaturvedi, 2017).

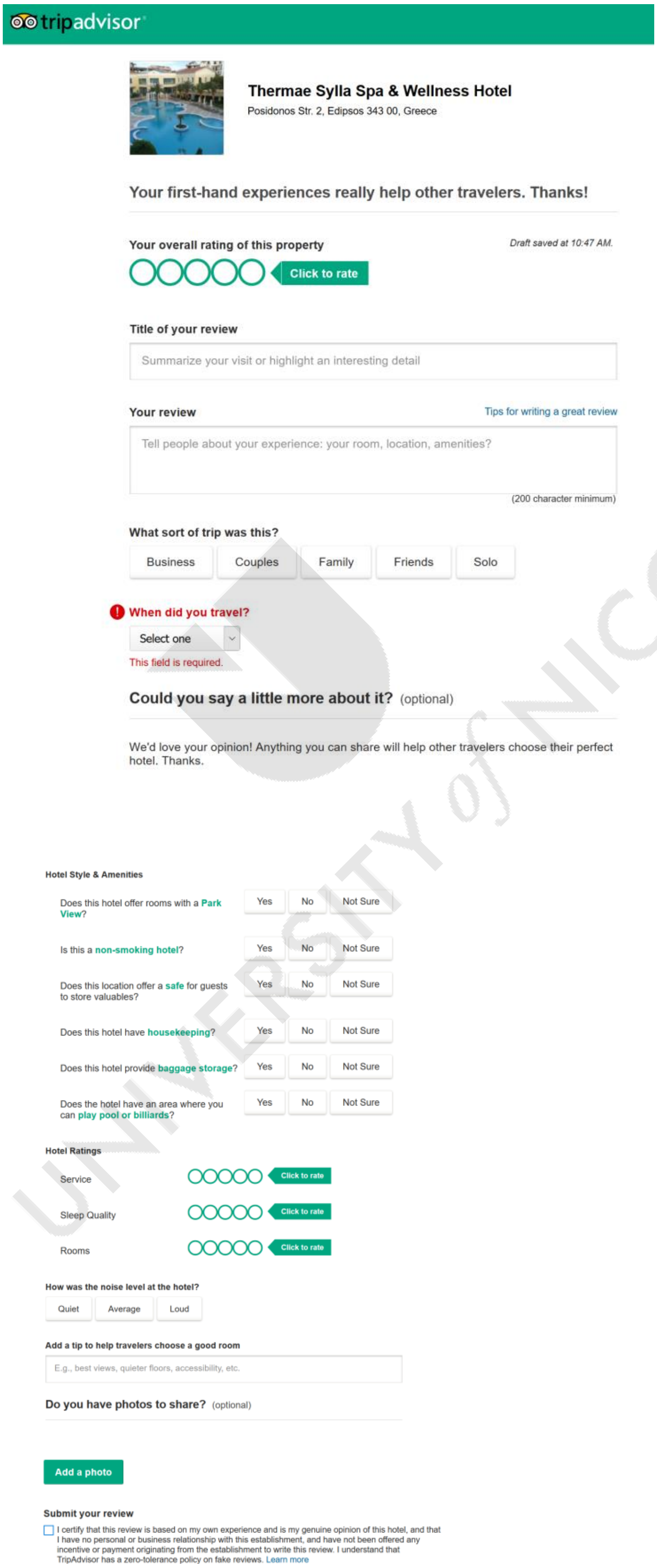
We understand that there has been a debate regarding the effectiveness and autonomy (if they can be used without additional information) of online reviews as a tool for service quality management. Hotel managers also continue to use questionnaires to evaluate service quality. To the author's best knowledge, no published study exists concerning managers' perceptions on these two tools. The first part of the research thus aims to address this gap by identifying what information the managers extract from each tool, what hotel needs this information covers, and if there is overlapping information. Thus, the literature review mentioned above leads to the investigation of how hoteliers perceive online reviews in comparison to survey quality assessment scales.

There has been a rising interest in incorporating traditional service quality instruments with eWOM. Although at the beginning of this research the only relevant study was Boon, Bonera and Bigi's (2014), there have been a few others recently studying this subject (Ukpabi and Karjaluoto, 2018; Palese and Usai, 2018; Rus et al., 2019; Gebremichael, 2019). According to Boon, Bonera and Bigi (2014), their work on HOLSERV+ allows hotel managers to make sense of eWOM while providing researchers with a tool to study perceived service quality. Their intention is not to replace service quality surveys, but rather to provide the first instrument to link online reviews with service quality as an additional easily accessible source of information (Boon, Bonera and Bigi, 2014). Rus et al. (2019) incorporated HOLSERV+ to study the hotel service quality in Borobudur, by analyzing the extracted information based on the 5 HOLSERV+ dimensions (employee, facility, surrounding, reliability and room). They used three different algorithms to classify the data and concluded that Naive Bayes is the most reliable for this work (Rus et al., 2019). Palese and Usai (2018) use a weakly supervised topic model to extract SERVQUAL, service quality dimensions from online reviews. They mention that responsiveness and empathy are the most discussed topics in their research while tangibles and assurance are discussed less.

On the contrary, studying the service quality dimensions of hotels in Tigray Gebremichael (2019) realizes that tangibility is an essential dimension for customers regarding service quality. In another recent study, Ukpabi and Karjaluoto (2018) employing Wu and Ko's (2013) three dimensions of hotel service quality to study culturally nuanced attributes, including security perceptions in specific African Countries, they tested SERVQUAL as an option for their study. They ended up rejecting it since, according to their tests on SERVQUAL responsiveness, assurance and empathy were not particularly evident in tourism reviews (Ukpabi and Karjaluoto, 2018) and concluded that HOLSERV items could offer more interesting insights in their study. The findings above in relation to Li, Ye and Law's (2013) conclusion that online customer reviews might provide additional service quality information relative to traditional quality assessment tools, bring us to the next sub-questions. Therefore, it is essential to research if online reviews provide additional information about service quality assessment. Moreover, to the author's best knowledge, there is no multi-dimensional model where online reviews can be classified into sentence-based level categorization of quality assessment scales. Consequently, it has not been investigated yet if eWOM reviews can be fitted to all the SERVQUAL and HOLSERV/HOLSERV+ scales item-level categorisation. Therefore, the thesis develops a multi-level categorization model in which online reviews can be classified. This model also includes all the items (sentence-based level) of SERVQUAL and HOLSERV scales. Fitting online reviews in this model makes it possible for the present thesis to investigate among others, if SERVQUAL and HOLSERV(+) categories can be identified in eWOM reviews and whether some of those categorisations are under-represented in customer-generated review content.

Boon, Bonera and Bigi (2014) specified a few limitations studied in their research. Reliability was a significant concern for Boon, Bonera and Bigi (2014) because, in their example, they extracted just a few online reviews and only for one hotel since they were constrained by manually copying the reviews. They suggest that the HOLSERV+ method and categorisation were necessary for the classification of online information. The advancements in machine learning might aid in diminishing these limitations, so this study is utilizing aspect classification analysis through convolutional deep neural network advancements, in order to apply SERVQUAL and HOLSERV(+) model categorisation to online review information. Based on the results, the study researches how well these models can be applied, and if there is any information missing from online reviews when it comes to the quality assessment scale dimensions and categorisation.

## *FIGURE 4: TRIPADVISOR REVIEW FORM*



tripadvisor

Thermae Sylla Spa & Wellness Hotel
Posidonos Str. 2, Edipsos 343 00, Greece

Your first-hand experiences really help other travelers. Thanks!

Your overall rating of this property

Draft saved at 10:47 AM.

Click to rate

Title of your review

Summarize your visit or highlight an interesting detail

Your review

Tips for writing a great review

Tell people about your experience: your room, location, amenities?

(200 character minimum)

What sort of trip was this?

Business | Couples | Family | Friends | Solo

When did you travel?

Select one

This field is required.

Could you say a little more about it? (optional)

We'd love your opinion! Anything you can share will help other travelers choose their perfect hotel. Thanks.

Hotel Style & Amenities

| | | | |
|---|---|---|---|
| Does this hotel offer rooms with a Park View? | Yes | No | Not Sure |
| Is this a non-smoking hotel? | Yes | No | Not Sure |
| Does this location offer a safe for guests to store valuables? | Yes | No | Not Sure |
| Does this hotel have housekeeping? | Yes | No | Not Sure |
| Does this hotel provide baggage storage? | Yes | No | Not Sure |
| Does the hotel have an area where you can play pool or billiards? | Yes | No | Not Sure |

Hotel Ratings

| | |
|---|---|
| Service | Click to rate |
| Sleep Quality | Click to rate |
| Rooms | Click to rate |

How was the noise level at the hotel?

Quiet | Average | Loud

Add a tip to help travelers choose a good room

E.g., best views, quieter floors, accessibility, etc.

Do you have photos to share? (optional)

Add a photo

Submit your review

I certify that this review is based on my own experience and is my genuine opinion of this hotel, and that I have no personal or business relationship with this establishment, and have not been offered any incentive or payment originating from the establishment to write this review. I understand that TripAdvisor has a zero-tolerance policy on fake reviews. Learn more

## 2.7 Research Problem and Thesis Statement

As already pointed out in this chapter, there has been a debate regarding the effectiveness and autonomy of online reviews as a service quality management tool. Researching managers' perceptions regarding online reviews and service quality assessment tools could clarify a few of these issues. To the author's best knowledge, no published study exists concerning managers' perceptions on these two tools. The first phase of the Thesis thus aims to address this gap by identifying how hoteliers perceive online reviews compared to traditional surveys.

Based on the discussion above, overcoming the weaknesses of individual online reviews, together with the possibility of identifying satisfaction and service quality information in eWOM has led researchers to work in the extraction of service quality dimensions from those reviews. Specifically, there are a few studies that research the possibility of correlating upper-level service quality dimensions (tangible, reliability Reliability, Assurance, Tangibles, Empathy, Responsiveness) dimensions (Gebremichael, 2019; Palese and Usai, 2018; Rus et al., 2019; Ukpabi, Dandison Olaleye, Sunday Mogaji, Emmanuel Karjaluoto, Heikki, 2018; Ukpabi and Karjaluoto, 2018; Boon, Bonera and Bigi, 2014; Duan et al., 2013; Li, Ye and Law, 2013). To the best of the author's knowledge, a study researching the possibility of categorizing and correlating eWOM unstructured information to each category of the quality assessment scale dimensions is yet to be published. Therefore, in the second phase, this Thesis first investigates on a survey-sentence-based level, the sub-dimensions provided in questionnaires in correlation to the information from an online reviews' corpus.

All in all, this Thesis investigates if online reviews can be fitted in quality assessment scales dimensions and sub-dimensions and proposes a fine granularity multi-dimensional quality assessment model for the Hospitality, Leisure and Tourism Sector that employs user-generated content (UGC) and transforms it to customizable structured information.

## 2.8 Conclusion

Chapter 2 initially presented the methodological approach for the literature review and then the preliminary work that led to the specific Thesis research. Subsequently, the Chapter discussed the theoretical framework related to word of mouth and electronic word of mouth as well as to satisfaction and service quality. The literature review provided detailed information on the importance of eWOM in travellers accommodation decisions. Moreover, it discussed in detail service quality tools and how they transitioned from SERVQUAL to HOLSERV and HOLSERV plus.  The literature review reveals the research gap presented in the last part of the Chapter and the derived research questions. The next Chapter presents the philosophical stand of this Thesis. Moreover, the Research Questions are presented together with the Research Aim and Objectives.

# CHAPTER 3 RESEARCH METHODOLOGY

## 3.1 INTRODUCTION

The previous chapter provided the theoretical and literature foundations of the Thesis. Moreover, it focused on the research gap that leads to the research questions that this Thesis investigates. In this Chapter, the first Section discusses the Research Aim, presents the Research Question and the Specific Research Questions of this Thesis, as well as the Research Objectives. The next Section presents the Philosophical Stand of this Thesis. Finally, the Methodological approach of both studies are presented. For the Managers' Perspectives, an email interview approach is chosen, followed by a content analysis that aided in extracting and synthesizing the results. The data mining study entails the extraction of data followed by the preprocessing of the extracted information. SEMEVAL's categorisation approach has been used in order to develop the training file of the algorithm. The process incorporated annotators, two expert linguists and an expert in the field of Tourism in order to ensure the validity of the results. After developing the training dataset and preparing the mined corpus, the data are fed to the convolutional neural network algorithm, which has been developed to tackle the classification problem. The model is evaluated using F-measure and validated using 10-fold cross-validation. The next Chapter will present the results of both studies.

## 3.2 RESEARCH AIM

The present research has a double purpose: on the one hand, to bring together the structured methodologies of Business Administration for assessing products and services with the almost unstructured approach of online commentaries of tourists in the area of Crete, and, on the other hand, to investigate possible extensions of these approaches that might lead to more insightful analytics of the Big Data of Tourism. To achieve a complete understanding of the field, the Thesis first investigates hoteliers and hotel managers' opinions in Crete related to survey questionnaires and online reviews as quality assessment methods. Furthermore, it correlates service quality dimensions to unstructured online reviews and then combines the dimensions of the complementary models of SERVQUAL and HOLSERV(+) to produce a more detailed model. Finally, the Thesis develops an enriched model with additional dimensions that are not present in the previous two models developing a new enriched and more insightful multidimensional model.

## 3.3 THESIS PHILOSOPHICAL APPROACH

As part of the research, the ontological and epistemological assumptions need to be clarified, as they affect the choice of data collection methods, analysis, and presentation and explanation of results. The research questions have to do with critical realist ontological assumptions regarding what kind of things exist. In this case, these concern the relationships between how user-generated content can be better explained using different qualitative and quantitative methods, and how one could help trigger those causal mechanisms that would produce eWOM content with higher explanatory power. In this section, some background information regarding CR is initially presented, and then the section provides insight into how CR informs the methodological analysis of this study.

### ONTOLOGICAL AND EPISTEMOLOGICAL APPROACH

Critical realism was developed by Ray Bhaskar, a British Philosopher in the late 70s and 80s, by combining transcendental realism and critical naturalism. Transcendental realism is a philosophy of science, whereas critical naturalism is a philosophy of social sciences. CR was developed to be an alternative to positivism and constructivism (Denzin and Lincoln, 2017), but combines ideas from both methodological schools in view of ontology and epistemology. CR functions as a general methodological framework for research but is not associated with any particular set of methods.

According to CR, ontology (what is real) is not reducible to epistemology (our knowledge of reality). Reality exists independently from human consciousness. Human understanding captures only a small part of a more profound and vast reality. Reality consists of three overlapping ontological domains/ modes of reality (Bhaskar, 1977; Delorme, 1999). The first is the empirical domain, which is the realm that one can experience directly or indirectly. These aspects of reality can be measured empirically and can often be identified by common sense. These aspects are analyzed and explained by human understanding. The second is the actual, that is, the aspects of the realm that occur, but may not be experienced. In this part of reality, the events that occur are usually different from those observed in the empirical realm (Danermark et al., 2002). The third domain is the real, which consists of causal structures and mechanisms that generate phenomena. These structures and mechanisms cause the events of the actual and empirical, and cannot be felt directly, but they can be inferred through empirical research and the development of theories. Since one can only have access to the first (empirical) reality; knowledge is biased and partial. Reality, however, has both transitive and intransitive dimensions. Transitives are those that depend on one’s activities (reviews, services, products, and more) and intransitive are those that are independent of human activity (i.e., gravity, sunset, and more). CR tries to explain and reach a deeper understanding of events through reference to causal mechanisms and the effects that can be observed or inferred through the iceberg realm. (see Figure 3).

The iceberg metaphor's different levels do not suggest that one part is more real than the other. Instead, the metaphor conveys that every part/level belongs to the same entity/reality and that reality is more extensive than one can realize. This metaphor illustrates what can a human's understanding of reality be and what the possibilities of scientific error might be. The natural world is not activity-dependent while social structures are, which means that causal mechanics can only be empirically identified through the activities they regulate. Thus, they can only be understood through observations at the empirical level (Bhaskar, (2008). The empirical level can thus be researched to comprehend this part of reality (the tip of the iceberg) and make inferences/assumptions regarding the actual realm of reality (Fletcher, 2017). On the other hand, some mechanisms are inactivated in the real domain or activated but are counteracted by other mechanisms, so they do not generate events in the empirical realm. Similarly, triggered events in the domain of the actual can not necessarily be observed/experienced in the empirical domain (Wynn, JR. and Williams, 2012).

According to CR, the world functions within a multi-dimensional open system. Events occur due to the interaction of structures, mechanisms, and human activities, and they do not just follow a pre-set order. Causal mechanisms do not predetermine the event, but rather, they operate in a multivariable environment, and the actual event is the result of this coexistence (Lawson, 1997). This means that it is more suitable to consider events as tendencies that took place as results of underlying causal mechanisms, than just empirical generalizations (Lawson, 2003).

CR suggests that explanations can always be revised, and the best explanations are those with the most significant explanatory power. Any given theory can be later rejected if another more convincing one is developed (Sayer, 2002). Therefore, from the explanations produced through research, those with the most significant explanatory power are obtained.

Research methods should be chosen based on the nature of the research problem. CR suggests that there are cases when a combination of qualitative and quantitative approaches might be the most effective one (Olsen, 2007). What matters in CR is how these qualitative and/or quantitative methods are used (Pratschke, 2003). On the one hand, quantitative methods create reliable descriptions and provide accuracy in comparisons. During the explanatory phase, quantitative methods can identify hidden patterns and correlations (Fletcher, 2017). Quantitative methods can as well indicate how causal mechanisms function under certain conditions (Mingers, 2004). On the other hand, qualitative methods can be used to give insight into complex situations and relations. Their characteristic of being open-ended allows unexpected events to arise at any given query. Those events might not be observable using quantitative methods.

We use these methods to define a phenomenon by creating/extracting observations of events and then use this definition as the basis for possible explanations.

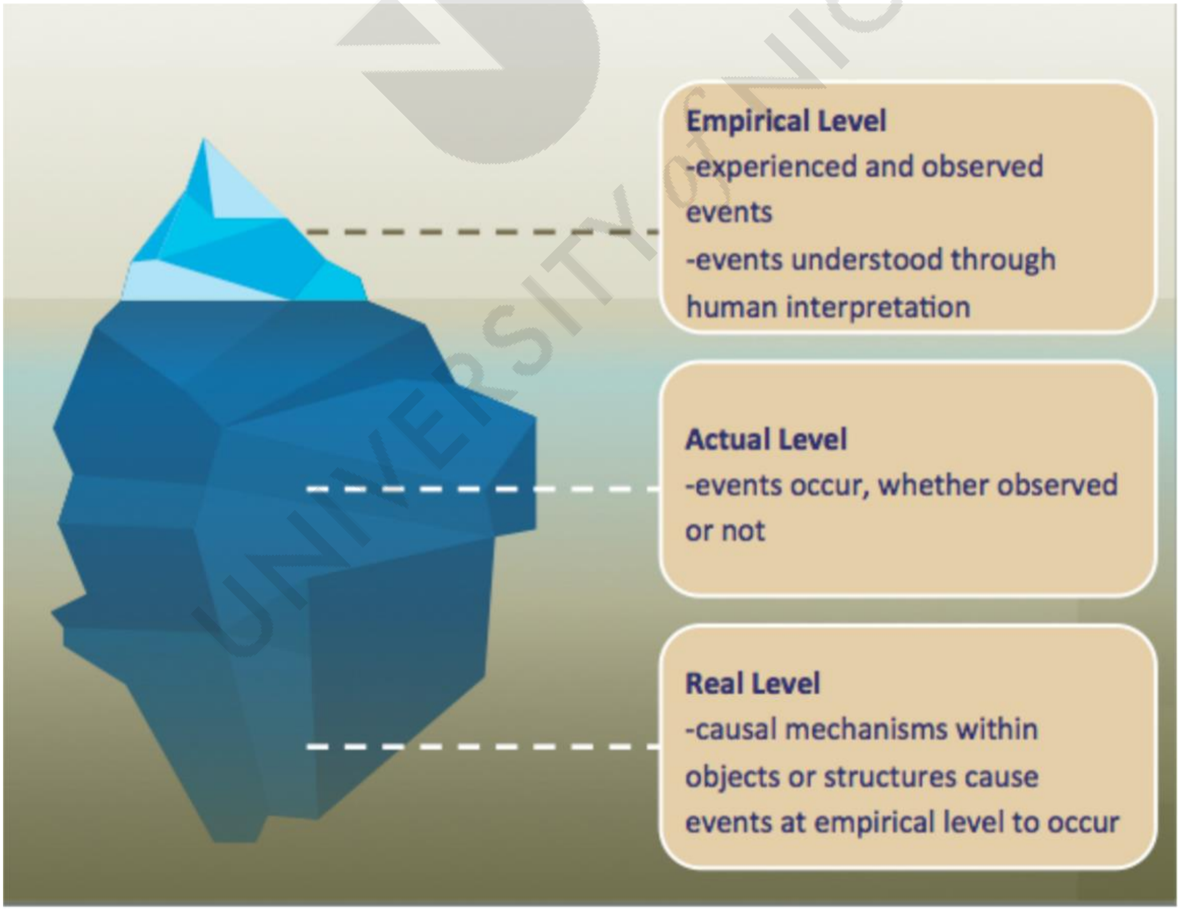



FIGURE 3. AN ICEBERG METAPHOR FOR CR ONTOLOGY AND EPISTEMOLOGY

Source: Fletcher (2017)

This thesis uses a triangulation mixed-method design with a sequential mixed-methods approach (Teddlie and Tashakkori, 2009). More specifically, the thesis initially collects qualitative data to identify hotel managers' perspectives. Then the research uses data mining to extract data for which both quantitative (descriptive analysis) and qualitative analysis (text mining) is performed (Teddlie and Tashakkori, 2009). Among the qualitative techniques used in this methodological approach, there is a quantitative technique, namely frequency counting. Although frequency analysis involves counting words, which seems to be a quantitative method, its data type is still qualitative (Morgan, 1993). Moreover, text mining's objective and criteria are compatible with those of qualitative research (Morgan, 1993). So, researchers have been using frequency techniques (i.e., frequency counting, frequency word map), topic modelling, and other techniques as supplementary qualitative research tools (Mcnaught and Lam, 2010; Nelson, 2017). In fact, in his contemporary computational approach to grounded theory, Nelson (2017) often uses frequency counting, managing in this way to incorporate massive amounts of data into theory-generating research.

Consequently, in this mixed method methodological approach, both qualitative (i.e., text analysis) and quantitative (i.e., frequency analysis) tools are utilised to observe the accessible empirical realm's information.

Reality is an open system. My need to observe the world independently, which can be from an external point of view, objective but at the same time socially constructive and subjective, is materialized through extraction of user-generated content, which consists of the observable events extracted from online sources. These events are the experiences that other humans created spontaneously (without my implication), triggering a series of other causal mechanisms in all realms of reality.

Taking the position of a critical realist, my intended strategy for inquiry is informed by the approach of qualitative methods. This approach aims to observe phenomena and deduct conclusions based on the extracted data and is conclusive to the literature gaps of the scientific field observed/studied.

This choice is further justified by the present study's aim, which seeks to bring together different instruments of observing reality. It is intended at first to focus on understanding the underlying mechanisms, which create the given behaviour of online reviewers, and the conditions, which create the circumstances for the events to take place and find possible explanatory approaches to the phenomenon of eWOM.

I am observing the theoretical framework based on the methodology needed to explain the events, which will provide deductively answers/observations to the research questions. The research questions have to do with critical realist ontological assumptions regarding an independently existing reality and the ability to observe the relationships through the events and experiences that are taking place, which in this case are the reviews of travellers' experiences, using and combining the available tools (i.e., HOLSERV plus scale with data mining techniques), in order to find that explanatory combination, through the research questions objectives, that best represents, explains the realization of the causal mechanisms (whether they belong to the real, actual or empirical realm) that collaboratory produced the empirical reality that is investigated.

In other words, the thesis ultimately seeks to research i) how user-generated content can be better explained using different qualitative and quantitative methods and ii) how other mechanisms (i.e., traditional survey tools) could participate in triggering those causal mechanisms that would produce eWOM content with greater explanatory power.

The observations with the most significant explanatory power are going to be the conclusive ones to the research questions. The study is mainly inspired by Bhaskar's (1977; Bhaskar, 2008) interpretation of reality, which assumes that one can never fully grasp reality' with one's senses. Only part of the underlying mechanism matrix can be seen, which triggers the events of reality, that might be observed.

**TABLE 1** PHILOSOPHICAL STAND

(as seen at Prof. Kaufman's presentation 03/11/2017)

| **Positivist paradigm** | **Phenomenological** |
|---|---|
| Observer is independent | ~~Science is driven by human interest~~ |
| Science is value-free | ~~Observer is part of what is observed~~ |
| The world is external and objective | The world is socially constructed and *tends to be subjective* |
| **Researcher here is:** | |
| Focusing on facts | in order to understand what is happening |
| ~~Formulate a hypothesis~~ | Formulate a research question<br>Develop ideas through induction of evidence |
| Focus on meanings | ~~Look for causality and fundamental laws~~ |
| (Look at the totality of each situation – cluster analysis?) | Reduce phenomena to their simplest elements |
| **Method** | |
| Large Samples | - |
| Frequency Analysis | Aspect mining<br>Sentiment mining |
| ~~Operationalize concept so they can be measured~~ | Use Multiple Methods to establish different views of phenomena |

## 3.4 Research Questions

What aspects of quality assessment scales (SERVQUAL, HOLSERV(+)) can be represented by online reviews?

### Specific Research Questions

1. How do hoteliers perceive online reviews in comparison to traditional surveys?
2. How can eWOM reviews be fitted to SERVQUAL, HOLSERV/HOLSERV+ scales dimensions and sub-dimensions?
3. What aspects of eWOM are not included in SERVQUAL and HOLSERV+?

4. Which additional categories rise from frequency analysis?
5. How can the information richness of the newly-developed model be improved, utilizing the frequency analysis findings?
6. How well does the novel-proposed fine-granularity multi-dimensional model fit eWOM?

## 3.5 SPECIFIC RESEARCH OBJECTIVES

1. Identify the opinions of hoteliers on traditional quality assessment tools and online reviews
    a. Comprehend how hotels perceive the information sources of service quality assessment scales and online consumer reviews.
    b. Get insight into the information that hotel managers retrieve from each tool mentioned earlier, and their perception and informational needs that might be left uncovered.
    c. Identify if there is differentiation or overlapping information between service quality questionnaires and consumer reviews on online travel platforms.
2. Develop a multi-level model to fit eWOM content to the Service Quality Scales categorisation in an upper level to a sentence-based level.
3. Research the possibility of underrepresented categories of SERVQUAL, HOLSERV(+) models
4. Use machine learning to fit online reviews in SERVQUAL and HOLSERV(+) categorisation
5. Perform FrequencyAnalysis on extracted online reviews and identify if there is additional quality assessment information provided from online reviews that is not captured in surveys.
6. Improve the proposed model by adding aspects based on the frequency analysis findings.
7. Apply the novel-proposed fine-granularity multi-dimensional model on eWOM reviews and discuss findings.

**TABLE 2 RESEARCH QUESTION, OBJECTIVE AND METHODOLOGY TABLE**

| Research supporting Literature | Main Research Question | Research Questions | Research Objectives | Methodology |
|---|---|---|---|---|
| Duan et al. (2013) point out the need to understand how online reviews affect the hotels' service quality approaches and, consequently, actions taken and their strategies.<br>Li, Ye and Law (2013) emphasize the need for researchers to study the role online reviews play within organisations as part of their service quality measurement system.<br>Lockyer (2005) indicates a gap between managers' perceptions of what is essential for guests and what guests actually perceive as important when choosing accommodation. | What aspects of quality assessment scales (SERVQUAL, HOLSERV(+)) can be represented by online reviews? | How do hoteliers perceive online reviews in comparison to traditional surveys? | Identify the opinions of hoteliers on traditional quality assessment tools and online reviews<br>a. Comprehend how hotels perceive the information sources of service quality assessment scales and online consumer reviews.<br>b. Get insight into the information that hotel managers retrieve from each tool mentioned earlier, and their perception and informational needs that might be left uncovered.<br>c. Identify if there is differentiation or overlapping information between service quality questionnaires and consumer reviews on online travel platforms. | Thematic Content Analysis |
| Li, Ye and Law (2013) suggest that customer reviews are based on open-ended questions (versus the fixed questions of quality surveys) they might provide with additional service quality information that service quality assessment scales do not cover | | How can eWOM reviews be fitted to SERVQUAL, HOLSERV(+) scales dimensions and sub-dimensions? | Develop a multi-level model to fit eWOM content to the Service Quality Scales categorisation in an upper level to a sentence-based level.<br><br>Research the possibility of underrepresented categories of SERVQUAL, HOLSERV(+) models | Data mining / Text Scrapping<br>Text pre-process and micro-content analysis<br>Development of the multi-level model<br>Development of Pre-Annotated Training File<br>Fit SERVQUAL, HOLSERV(+) categorisation to Aspect-based Sentiment Analysis training dataset |
| Berezina et al. (2016) remark that online reviews support the basic structure of service quality scales, which separate tangible (i.e., room furnishing) from intangible (i.e., staff services) aspects.<br>Berger (2014) suggests that traditional promotional tactics that have been applied to the offline world can provide us with new insights regarding drivers of consumer behaviour.<br>Boon, Bonera and Bigi (2014) suggest that the HOLSERV+ model should be applied to other regions so that the model could be cross-tested for reliability.<br>Palese and Usai (2018) use a weakly supervised topic model to extract SERVQUAL, service quality dimensions from online reviews.<br>SERVQUAL responsiveness, assurance and empathy were not particularly evident in tourism reviews (Ukpabi and Karjaluoto, 2018) | | Which additional categories rise from frequency analysis? | Perform FrequencyAnalysis on extracted online reviews and identify if there is additional quality assessment information provided from online reviews that is not captured in surveys. | Frequency analysis<br>Extract most used words<br>Word cloud |
| | | How can the information richness of the newly-developed model be improved, utilizing the frequency analysis findings?<br><br>How well does the novel-proposed fine-granularity multi-dimensional model fit eWOM? | Improve the proposed model by adding aspects based on the frequency analysis findings.<br><br>Apply the novel-proposed fine-granularity multi-dimensional model on eWOM reviews and discuss findings. | Compare annotated information with the descriptive information and create new categorisations for annotation.<br>Develop new pre-annotated training file<br>Machine Learning classification with Aspect-based Sentiment Analysis annotation through supervised training, Cross data validation |

## 3.5 METHODOLOGICAL FRAMEWORK

### 3.5.1 MANAGERS' PERSPECTIVES ON CONSUMER QUALITY EVALUATION TOOLS

In order to have a more accurate view of the field, the Managers' Perspectives on consumer Quality Evaluation Tools is studied.

#### CONTENT ANALYSIS

This next stage involves extracting the email interview responses and importing them in NVivo for analysis. The qualitative methodology used in this phase is content analysis.

According to Li, Ye and Law (2013), content analysis was initially developed and applied during the 1940s, and it has been frequently used as a research technique for more than 60 years now. "Content analysis is a research method that provides a systematic and objective means to make valid inferences from verbal, visual, or written data in order to describe and quantify specific phenomena" (Downe-Wamboldt, 1992). Therefore content analysis leads to valid and replicable inferences from texts systematically and objectively (Li, Ye and Law, 2013). This methodology has been employed in Hospitality, Leisure and Tourism research by different researchers (Camprubí and Coromina, 2016).

Content analysis is not bound to a specific science or a particular philosophy, and it can be applied as a qualitative or quantitative method (Bengtsson, 2016). In any case, content analysis reduces the amount of information seized, identifies and clusters the information in categories and pursues to make meaningful inferences through this process (Bengtsson, 2016). The process is content analysis

Inspired mainly from Erlingsson and Brysiewicz's (2017) work, this research follows a manifest content analysis that involves a few steps presented next. Each of these steps has been revisited a few times to ensure the quality and reliability of the analysis. Table 3 (see next page) presents a sample of the coding categories and information.

Validity and reliability are the two main concerns when it comes to research in general. When performing any kind of research, human mistakes are always possible. The researcher has the responsibility to ensure the study's reliability and validity (Bengtsson, 2016). In qualitative studies, "validity means that the results truthfully reflect the phenomena studied, and reliability requires that the same results would be obtained if the study were replicated" (Bengtsson, 2016). To ensure the validity and reliability of the process, two coders were trained to guarantee that they had knowledge of the rules and procedures and then performed the coding process as well (Camprubí and Coromina, 2016; Bengtsson, 2016; Erlingsson and Brysiewicz, 2017). Afterwards, differences in coding of phrases were discussed, and ambiguious phrases were discarded from the data. For instance, in response to "How reliable is the information provided by questionnaires in comparison to online reviews? Please, comment", Z.A. responded, "They are more reliable". In this case, I had inferred that since Z.A. does not use surveys anymore, they believe that Online reviews are more reliable. However, the second coder argued that there might be other reasons for abandoning this method, i.e., they might have switched due to lower cost. We concluded that since they do not explicitly specify which tool is more reliable, we cannot make any reliable inferences. Finally, the following stages were used for this research.

Decontextualization: Repeatedly read the questionnaire answers as a whole. This step aids in familiarizing oneself with the data and create a sense of the complete passage. While gaining an initial understanding of the ideas presented, the researcher develops some initial ideas on the coding. Then, the answers were divided into smaller sections, the meaning units. These initial codes changed significantly during the next steps of the process. The codes were created deductively based on the research questions, the interview questions, having in mind the meaning units, that is, the way the participants responded and the under-analysis information of the study as a whole.

Recontextualization: After the meaning units have been created, the whole text was re-read together with the meaning units. The unmarked text has been either added to meaning units or discarded as unhelpful.

Categorization: In this stage, the extended meaning units are condensed in smaller meaning units without losing meaningful content from the initial unit. Afterwards, the meaning units are clustered in codes. In this stage, the intention is to code the information, which gives the meaning units labels of one to two words long, describing the unit as precisely as possible. Manifest content analysis is usually performed by creating a coding system (Bengtsson, 2016) deductively.

## INTERVIEWS

The initial approach to perspective participants took place through email, where a cover letter introduced the research topic and aims. Later, telephone contacting took place for each hotel to arrange a meeting (which would be in person, through Skype or phone call). However, although this study's initial intention had been to work with interviews, eventually, after coming in contact with hoteliers and hotel managers, they repeatedly denied engaging in an interview, and they persisted in having the questions written. Consequently, the study changed the method from structured oral interview to structured email interview (Martini and Buda, 2019; James, 2007). Among the main benefits of using online research methods, is that it becomes easier to reach difficult to access participants due to constraints like money, distance, and time (James, 2007). One disadvantage of this approach is that it has been difficult to recontact participants (and get responses) on answers that might need further details or clarification.

The following information was provided in the email: the guidelines, the criteria for someone to participate in the research, and a link to the interview questions. The interview questions are present in Appendix A. Google forms tool was used to present the questions to the participants.

## CRITERIA AND PARTICIPANTS SELECTION

In order for a hotel manager or hotelier to participate in the email interview, two conditions had to be met. The establishment should use or have used questionnaires for assessing service quality. The second criterion is that the establishment must have a presence in online travel portals and should be aware of the reviews concerning their organisation. The survey participants are hotel managers and hoteliers from Crete. Their contacts (telephone numbers and emails) are obtained randomly through hotel managers and hoteliers' associations and personal contacts. For this email interview, more than 120 hotels were contacted through email, and at least 50 of these were also contacted by phone calls. The participants are presented in the "Interview Participants" section of this chapter.

| meaning unit | condenced meaning unit | code | code meaning | categories/themes |
|---|---|---|---|---|
| | | | | |
| If questionnaires are created properly, and they can measure what they should, then they might be the best source of information (or the most straight to the point), in comparison to online reviews where we have a description. Comments, of course, can measure experiences related to service and describe/justify decisions that can not be given by questionnaires (usually the behavior of a certain member of the stuff etc.) | online reviews provide a description | D.1. Comp. R + | OR positives | Comparison of Surveys and Online Reviews |
| | surveys are better when properly developed | D.1. Comp. S + | Surveys positives | Comparison of Surveys and Online Reviews |
| | online reviews can assess experiences in relation to service | D.1. Comp. R + | OR positives | Comparison of Surveys and Online Reviews |
| | online reviews can provide explanations to customers' decisions | D.1. Comp. R + | OR positives | Comparison of Surveys and Online Reviews |
| | explanations to customers 'decisions cannot be provided by questionnaires (i.e. employee behavior) | D.1. Comp. R + | OR positives | Comparison of Surveys and Online Reviews |
| When the sample is big, then you can understand the tendencies from one hand, and on the other hand you can identify the actual assessment of the services provided. The online reviews are given based on experiences and the DON'T correspond always to the truth, because the visitor compares unrelated things (for example a hotel that he paid in Dubai of season VS 5* Hotel in Rhodes).<br><br>Today there are platforms (i.e. review pro) that can help in the analysis of comments based on the frequency of appearance of repeated subjects | big sample can provide the tendencies | D.1. Comp B N | both neutral | Comparison of Surveys and Online Reviews |
| | big sample can provide the actual services assessment | D.1. Comp B N | both neutral | Comparison of Surveys and Online Reviews |
| | online reviews are related to personal experiences, so they do not always correspond to truth | D.1. Comp. R - | OR negatives | Comparison of Surveys and Online Reviews |
| | online platforms (i.e. review pro), provide analytics on subjects | D.1. Comp R + | OR positives | Comparison of Surveys and Online Reviews |

**TABLE 3 EXAMPLE OF THE CODING PROCESS**

The interview questions are based on the theoretical assumptions from literature and create a framework and provide the basis for which the material is divided. Consequently, the content analysis themes are more or less known from the beginning of the analysis. During the analysis and report, one change that took place is the thematic areas of adaptability, quality, and reliability of information were joined in one theme because the responses were referring to the similar qualities and issues of the tools. The analysis codes were also created at the beginning of the analysis based on the themes and research questions. As a result, in the categorisation phase of the analysis, the meaning units are connected to the appropriate codes and therefore, to their related themes.

Compilation: Once the categorisation phase is completed, the presentation phase begins. In the analysis, the researcher considers all the collected information from a neutral perspective and gradually presents the analyzed content through each derived thematic category (Bengtsson, 2016).

Each step of the aforementioned process described by Erlingsson and Brysiewicz (2017), was revisited continuously until Condensation, Codes, Categories, and Themes all reflected in the best possible way the answers of the survey participants. This work's results are presented and then synthesized to get a deeper understanding of hotel managers' and hotel owners' views.

### INTERVIEW PARTICIPANTS

The email interview participants are hotel managers and hoteliers from Crete. Their contacts (telephone numbers and emails) are obtained through hotel managers and hoteliers' associations and through personal contacts. For this survey, more than 120 hotels were contacted through email by which at least 50 were also contacted by phone. Finally, 15 hotels participated in the Interview during the period 20-28 November 2018. Since this is an anonymous email interview, the accommodation organisations' initials are provided, as seen in table 4. Table 4 also provides a basic profile of each hotel, as seen in TripAdvisor.

| Accommodation Participants | Hotel Style | Hotel Class | Number of rooms | Price range |
|---|---|---|---|---|
| Ac. | Luxury, Business | 4 | 72 | 70 - 180 |
| Ag. | Hotel Apartments | 2 | 8 | 95 - 100 |
| Ap. | Hotel Studios | 2 | 97 | 45 - 135 |
| E.R. | Luxury | 4 | 12 | 215 - 285 |
| Em. | Hotel Apartments | 3 | 13 | 45 - 80 |
| G.C. | Luxury Boutique Hotel Residences | 5 | 3 | 2.195 - 2.315 |
| H.B. | On the Beach, Luxury | 4 | 67 | 45 - 150 |
| Id. | Hotel Apartments | 2 | 30 | 35 - 87 |
| K.R. | Business, Family, Romantic, Luxury | 5 | 346 | 150 - 3525 |
| L.P. | On the Beach, Spa, Family, Romantic | 4 | 575 | 170 - 575 |
| O.P.R. | Spa, On the Beach, Luxury, Family, Romantic | 5 | 345 | 90 - 205 |
| R.C.V. | Spa, Business, Family, Romantic, Luxury | 5 | 202 | 265 - 1080 |
| S.B.C.R.S. | Resort and Spa | 5 | 161 | 65 - 163 |
| S.M.N. | Studios | 2 | 8 | 30 - 110 |
| Z. | Studios | 2 | 7 | 45 - 63 |

**TABLE 4** PARTICIPANTS AND THEIR PROFILE (AS SEEN IN TRIPADVISOR ON 3RD OF DECEMBER 2019)

One contradiction that arose through this work is that on the one hand, R.C.V. states that they prefer questionnaires because online reviews usually take place a while after the stay, in comparison to surveys that take place while the customer is in the hotel (S.B.C.R.S.). This means that the memory of customers' experience has fainted (Id.). On the other hand, Ac. and G.C.S. hotels argue that usually online reviews take place after the customers have left the hotel and they have the composure to do an objective assessment of their stay. Probably, both situations co-exist, and each practice can impact differently on the accommodation provider's ability to assess service quality and respond to visitor's needs. In this case, one solution could be to encourage visitors to express their feelings and experience during their stay, through an online review or otherwise.

## 3.6 METHODOLOGICAL APPROACH OF DATA MINING STUDY

### DATA COLLECTION FOR DATA MINING

At this stage, data are extracted using scraping software (i.e., Content Grabber), and a database of online reviews from hotels of the region of Crete is created. Samples of online reviews have been taken and analyzed to assess and test the reliability of the methods and models to be used in order to make the final choice.

Online reviews are collected from TripAdvisor, a platform that was founded in 2000 and is considered to be the largest travel review site with more than 860 million reviews covering 8.7 million accommodations, restaurants, airlines, and attractions worldwide, and a monthly average of 463 million unique visitors (TripAdvisor, 2020). TripAdvisor has been used in research to study the role of social media in the hospitality, leisure and tourism field, including the accommodation sector (Torres, Milman and Park, 2018), the restaurant sector (Bowden and Dagger, 2011), and destination image (Tamajón and Valiente, 2015). Additionally, some studies of TripAdvisor researched the reviews' rankings and credibility (Jeacle and Carter, 2011).

The scrapping software is trained by creating an 'agent' that contains all the rules and commands to extract the exact information needed from each review, user, and accommodation. This process of retrieving semi-structured content from the web, in a markup language like HTML, XHTML, PHP, and more, following specified rules is called web scraping. The 'agent' is the scraping framework uploaded to the scraper application, which contains the rules, navigation techniques, website information, and commands that make possible the specialized extraction of data.

### TEXT PRE-PROCESSING

The text reviews that have been downloaded require a series of text pre-processes before they can be analyzed using text mining. Text pre-processing consists of several stages applied in accordance with the needs of the research. Specifically, the stages of text pre-processing include spelling normalization, filtering by removing unnecessary words and punctuations, word and phrase separation, lemmatization (grouping together the varied forms of each word so they can be analyzed all together as a single item) case and character normalization, and more. All stages are conducted through appropriate software each time (i.e. Microsoft Office).

One of the main disadvantages of online reviews, which has become obvious during the last decade, are fake reviews. Research on this field seems to efficiently minimize the phenomenon with supervised and unsupervised algorithms (Fontanarava, Pasi and Viviani, 2018; Stubkjaer, 2014). Moreover, the website from where the data have been extracted, TripAdvisor, has developed a sophisticated tracking system which identifies fake and biased (negative and positive) reviews and deletes them, while a dedicated team of investigators pursues companies and individuals that sell or post them (TripAdvisor, 2020). Despite this, based on the research on the field (Sanliöz Özgen, Kozak and John Bowen, 2015) and based on the qualitative study presented above, hotel managers seem to find online review channels trustworthy and practical tools to monitor. Li, Ye and Law (2013) state that hotels can achieve a reliable systematized assessment of service quality systems by utilising these new technologies and methodologies. One of the main ways to identify and eliminate fake reviews, when it comes to reviewer centric features (Neha S. Chowdhary and Anala A. Pandit, 2018) is by identifying the identical reviews in a corpus. Therefore, although it is out of the scope of this research, in order to receive more reliable results on the reviewer's discussed dimensions, we added one more step to the text pre-processing methodology, which is to identify and eliminate all duplicated reviews (Jindal and Liu, 2008; Neha S. Chowdhary and Anala A. Pandit, 2018; Kumar and Shah, 2018; Martens and Maalej, 2019; Kumar and Shah, 2018, 2018).

## ASPECT-BASED SENTIMENT ANALYSIS

As seen in the literature review on Machine Learning presented in chapter 2, categorisation problems can be approached with either an unsupervised clustering or supervised classification algorithms (Stivaktakis and Kokkinaki, 2020). Since the thesis investigates the possibility of creating a multi-level categorization based on service quality scales, the user-generated reviews corpus will need to be fitted to those categorisations. Therefore as will be presented in more detail in this section, the most efficient approach would be to develop a supervised seed-based aspect-classification model which will be trained based on an annotated corpus that will be fed to a deep neural network algorithm (Stivaktakis and Kokkinaki, 2020).

Before discussing the Aspect-based Sentiment Analysis (ABSA) Methodology, Sentiment Analysis and Aspect-based classification is discussed, because ABSA is based on these two methodologies.

***SENTIMENT ANALYSIS***

The next step is to determine the sentiment of every aspect that has been defined in the previous stages using the opinion mining approach. Recently, there have been many academic studies on sentiment-based classification (Markopoulos et al., 2015). Sentiment analysis or opinion mining is the process of using text analytics to extract negative or positive polarity of written text (Razia Sulthana, Jaithunbi and Sai Ramesh, 2018; Wilson, Wiebe and Hoffmann, 2005). Sentiment analysis can be applied to different levels of items, including document, sentence, and aspect level of text (Weismayer, Pezenka and Gan, 2018). The purest form of sentiment analysis consists of the document-level analysis, where the algorithm assesses the polarity of the whole document (Feldman, 2013; Pang and Lee, 2008; Pang et al., 2002).

In many cases, studying the overall polarity of a document is not enough. There are many instances where different levels of polarities can be identified in the document, in a paragraph, or even on the sub-sentence level. Some of the aspects can be positive, neutral, or negative.

Except for the text size approach, sentiment analysis can be viewed from the approach of the different methods that can be used. In general, there are two methods used to work on sentiment-based approaches, machine learning, and lexicon-based (Bing, 2016).

The researcher feeds/trains the algorithm with training data before the actual data are applied in the machine learning approach. The learning phase in machine learning can be either supervised or unsupervised. Supervised machine learning requires two pre-annotated datasets (training and test) to be provided to the algorithm at the beginning of the process. During this phase, the first dataset is used to train the classifier, while the second is to test the classifier's performance. The most common techniques used to train the classifier are Naïve Bayes (NB), Maximum Entropy and Support Vector Machine (SVM) (Pang et al., 2002; Boiy et al., 2007). Pang et al. (2002) were the first to work in semi-automatic sentiment classification, using supervised learning at a document level approach. They compared the three algorithms above, concluding that Support Vector Machine gives better results than the other two methods. The main drawback of supervised machine learning is that it requires big pre-training and testing datasets, making it challenging to create annotated data for different studied areas or/and languages.

Unsupervised machine learning techniques classify data into different categories using clustering algorithms (i.e., K-Means). During unsupervised classification, process Pointwise Mutual information and Semantic Orientation (the evaluative character of a word) can be used (Turney, 2002). In semantic orientation, two pre-chosen words (bad, inferior) in combination with a text corpus are utilised. The semantic orientation of the phrases is processed with their association with those two words. Calculating the average of the semantic orientation of the phrases gives us the overall sentiment of the document. Unsupervised learning is more cost and time effective since it does not need the pre-trained data. On the other hand, supervised learning has higher precision rates that unsupervised learning.

The Lexicon approach is based on the idea that the polarity of a phrase, sentence, or document, is the summation of the individual polarities of words and/or phrases. By using prespecified dictionaries (automatically or manually created), i.e., SentiWordNet, the Lexicon based analysis finds semantic orientation (positive, neutral, negative) of the given text. Weights are used in order to identify the strength of the words except for their polarity. Sentiment Lexicons can be created either by using Dictionary-based or Corpus-based data. Lexicon based analysis provides the advantage of being domain-independent, while dictionary-based approach uses online dictionaries (i.e., WordNet) and a small set of pre-chosen scaling words. A typical process is to create a group of a dataset of words manually with known orientations and then grow this set by searching the online dictionary for their synonyms and antonyms. The new words are added to the dataset and the process restarts. The process is complete when there are no new words to be added to the dataset.

On the other hand, the corpus-based approach is based on specific syntactic or reoccurrence patterns. A starting dataset of adjective opinion words is used to search for other opinion words in a corpus, also using specific constraints (eg. the conjunction word AND gives words of similar orientation). (Ashna and Sunny, 2018).

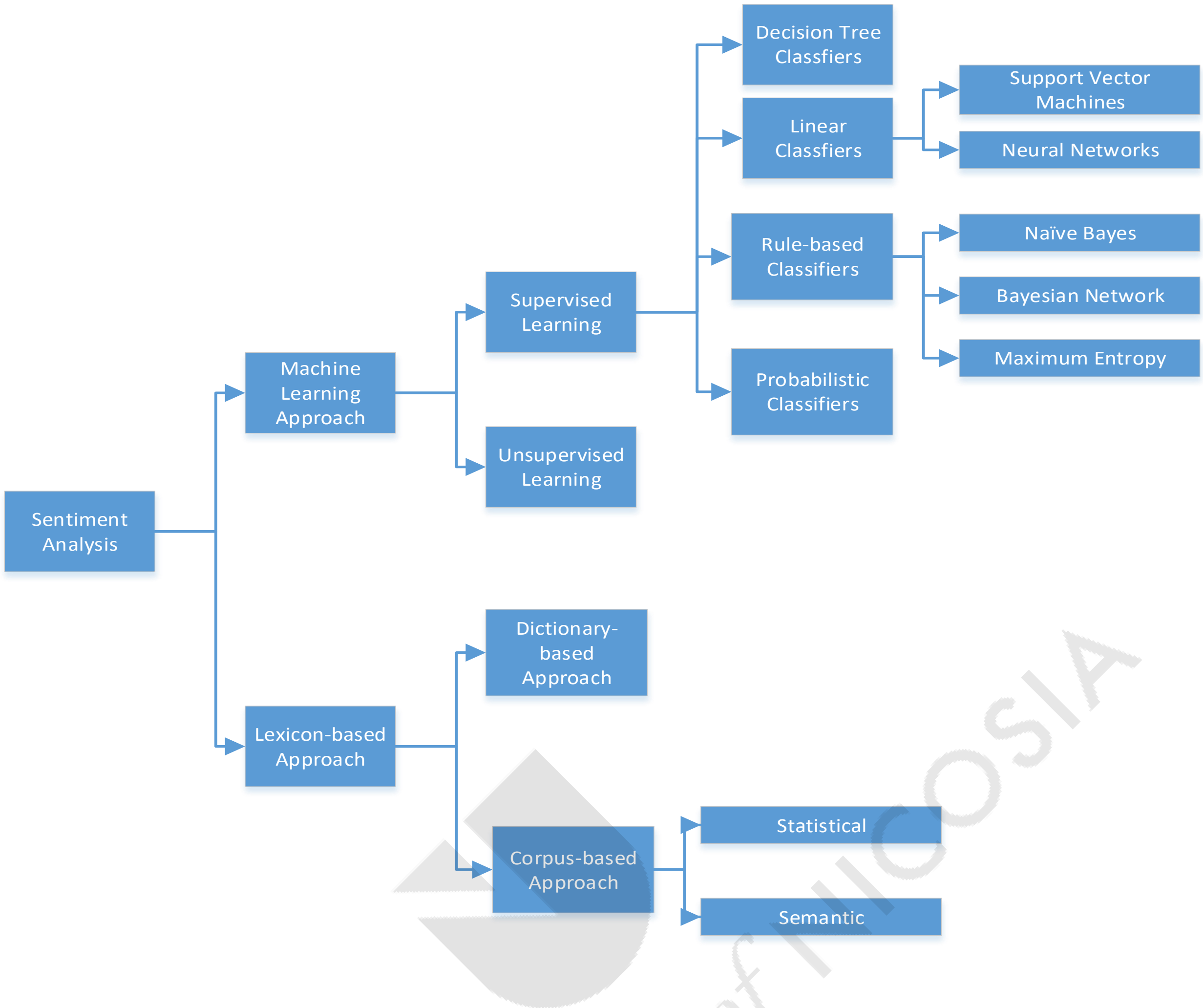



**FIGURE 5 SENTIMENT CLASSIFICATION TECHNIQUES** (as seen in Medhat, Hassan and Korashy (2014))

### *ASPECT CLASSIFICATION*

In parallel to sentiment analysis, we need to do the aspect classification of the researched information. The results of the aspect classification (Stivaktakis and Kokkinaki, 2020) are the main focus of this research since as presented in the literature review, they provide us with the occurrence of dimensions, which are going to lead us to answers regarding the research questions.

In general, aspect classification has been classified into three main categories, that is topic models, rule-based models, and seed-based models (Jiménez-Zafra et al., 2016). In rule-based models, the aspect identification is closely correlated with the identification of frequency occurrence and importance score. For instance, Jiménez-Zafra et al. (2016) create a bag of words with the aspect terms based on their frequency of appearance. Other scholars have a rank based methodology to extract and classify their data into different aspects (Muangon, Thammaboosadee and Haruechaiyasak, 2014). Ray and Chakrabarti (2019) have also applied the rule-based method, utilizing the power of deep neural networks to extract the desired aspects. Rules-based approaches are very effective. A disadvantage of adopting this methodology is that rule-based approaches can produce a limited number of rules, which makes it challenging to identify infrequent aspects (Afzaal, Usman and Fong, 2019).

Seed based models identify aspects by utilizing the grammatical connection between the reviewed words with the seed ones. For instance, Boon, Bonera and Bigi (2014) used the most reviewed categories in accommodation reviews to create the aspects of their HOLSERV+ model. Also, Colhot et al. 2014) created a seed pool based on each aspect of the five most-discussed topics in reviews. Similarly, Kayaalp (2017) used food, ambience, service, and price as the most discussed topics in restaurant reviews. Then he indexed the words in reviews, and finally, they categorized these words based on the initial four aspects (Millie et al., 2017). A limitation of the rule-based methodology is that they require extensive domain knowledge for the seeds and aspect classification to take place (Afzaal, Usman and Fong, 2019). Additionally, the extracted aspects (i.e., food, price, ambience, and service) are limited and thus not enough to adequately cover a whole domain (Afzaal, Usman and Fong, 2019).

Topic model models are based on the assumption that sentiments are combined from different topics, and each topic is a probabilistic distribution of a variety of words (Afzaal, Usman and Fong, 2019). Shams and Baraani-Dastjerdi (2017) used the latent Dirichlet allocation model (LDA) to extract aspects, incorporating knowledge from specific domains. They achieved that by finding the co-occurrence relations in reviews and then incorporating these relations as prior knowledge to their model.

### *ASPECT-BASED SENTIMENT ANALYSIS (ABSA)*

Aspect-based Sentiment Analysis combines the two methods mentioned above of Aspect-based models with sentiment analysis, achieving a more in-depth analysis of information through combining the classification of data with the identification of each case’s sentiment (Stivaktakis and Kokkinaki, 2020). In these terms, researchers have been proposing a lot of different models that produce outstanding results. A lot of work has been achieved through the International Workshops on Semantic Evaluation (Pontiki, M., Galanis, D., Papageorgiou, H., Manandhar, S., and Androutsopoulos, I., 2016; Pontiki et al., 2016; Pontiki and Pavlopoulos, 2014). Pontiki and Pavlopoulos (2014) developed an annotation scheme that has been utilised in many research studies. They extracted unigram features from sentences and then specified the aspect categories with integer-valued functions (Pontiki et al., 2016; Pontiki, M., Galanis, D., Papageorgiou, H., Manandhar, S., and Androutsopoulos, I., 2016). Followingly, they trained a machine learning classifier on the extracted features and made predictions of the test data, using the golden train dataset, which had been labelled by different annotators. With this model, they achieved 78.69% accuracy (Pontiki et al., 2016). Mohamad Syahrul Mubarok, Adiwijaya and Muhammad Dwi Aldhi (2017), classified restaurant reviews in different aspects using a naïve Bayes model. In their model, they pre-processed the reviews in order to remove any irrelevant information and transformed the words into POS tags (Mohamad Syahrul Mubarok, Adiwijaya and Muhammad Dwi Aldhi, 2017) Then they identified the most relevant words with the aid of chi-square, and finally, they implemented naïve Bayes classifier to categorize the reviews of each aspect into their sentiments (Mohamad Syahrul Mubarok, Adiwijaya and Muhammad Dwi Aldhi, 2017). Mohamad Syahrul Mubarok, Adiwijaya and Muhammad Dwi Aldhi (2017) achieved 77% accuracy in their aspect-based sentiment analysis. Afzaal and Usman 2016, proposed an Aspect-based Classification method where they collected data from Twitter; consequently, they extracted the aspects and trends. Then they identified the polarity of trends and aspects so that they could later classify the tweets as positive or negative. Karim et al. (2019), proposed a hotel recommendation system that is based on the hybrid sentiment analyzing system. This system utilises both supervised and lexicon analyzers and a Dirichlet allocation classifier which extracts aspects mentioned in reviews. Hanratty (2019), used word embeddings for aspect and sentiment seeds to categorize the information from two data sets. Wallaart and Frasincar (2019) use the SemEval 2015 and SemEval 2016 data for their aspect-based opinion model. They incorporate a rotatory attention mechanism (LCR-Rot), with two features. The first changes the order of operation of the rotatory attention mechanism, and the second runs over the first mechanism for multiple iterations.

## DETERMINING HOTEL ASPECTS / DIMENSIONS USING THE HOLSERV MEASURE

To proceed with the analysis, the categorisation scheme is initially customized, then the annotation phase takes place, and later the analysis stage. In this stage, the aspects and the categories that will be used are determined. This section presents an overview of how the service quality has been approached by SERVQUAL and HOLSERV/HOLSERV+, and then describes the train data's annotation.

In their work Mei, Dean and White (1999), they develop HOLSERV scale, where they keep all the items provided from SERVQUAL scale and add eight more items as provided in the next figure. This direct link of each sub-dimensions has been utilised from this thesis to keep and relate all the dimensions and sub-dimensions of both scales.

| No. | Basic wording | Origin | Grouping |
|---|---|---|---|
| REL1 | Promises to provide a service and does so | SERVQUAL | Reliability |
| REL2 | Shows dependability in handling service problems | SERVQUAL | Reliability |
| REL3 | Performs the service right the first time | SERVQUAL | Reliability |
| REL4 | Provides services at the time it promises to do so | SERVQUAL | Reliability |
| RES1 | Tells guests exactly when the services will be performed | SERVQUAL | Responsiveness |
| RES2 | Gives prompt service | SERVQUAL | Responsiveness |
| RES3 | Always willing to help | SERVQUAL | Responsiveness |
| RES4 | Never too busy to respond to guests' requests | SERVQUAL | Responsiveness |
| ASS1 | Instils confidence in guests | SERVQUAL | Assurance |
| ASS2 | Guests feel safe in the delivery of services | Customised | Assurance |
| ASS3 | Guests feel safe and secure in their stay | New | Assurance |
| ASS4 | Polite and courteous employees | SERVQUAL | Assurance |
| ASS5 | Have the knowledge to answer questions | SERVQUAL | Assurance |
| ASS6 | Have the skill to perform the service | New | Assurance |
| EMP1 | Gives individual attention | SERVQUAL | Empathy |
| EMP2 | Deals with guests in a caring fashion | SERVQUAL | Empathy |
| EMP3 | Has guests' best interests at heart | SERVQUAL | Empathy |
| EMP4 | Understands guests' specific needs | SERVQUAL | Empathy |
| TAN1 | Equipment, fixtures and fittings are modern looking | SERVQUAL | Tangibles |
| TAN2 | Facilities are visually appealing | Customised | Tangibles |
| TAN3 | Neat and professional employees | SERVQUAL | Tangibles |
| TAN4 | Materials are visually appealing | SERVQUAL | Tangibles |
| TAN5 | Fixture and fittings are comfortable | New | Tangibles |
| TAN6 | Equipment and facilities are easy to use | New | Tangibles |
| TAN7 | Equipment and facilities are generally clean | New | Tangibles |
| TAN8 | Variety of food and beverages meet guests' needs | New | Tangibles |
| TAN9 | Services are operated at a convenient time | SERVQUAL | Tangibles |

**FIGURE 6 SERVQYAL – HOLSERV CORRELATION**

In Boon's study, HOLSERV+'s dimensions are based on the HOLSERV scale; they are adapted from SERVQUAL scale, to allow distinctions between different dimensions. Specifically, (Boon, Bonera and Bigi, 2013) used dimensions differently by enriching the tangibles dimension (breaking in into three other dimensions: Room, Facilities, and Surroundings) and adding two more dimensions. In this way, the HOLSERV+ dimensions were made more distinctive and more readily applicable. This made scoring along with the questions distinctive and straightforward. Table 5 shows the SERVQUAL dimensions, and Table 6, the HOLSERV and HOLSERV+ dimensions.

Table 5 SERVQUAL Dimensions (Xiang and Tussyadiah, 2014)

| Dimension | Description |
|---|---|
| Tangibles | a. Physical facilities, equipment, and appearance of personnel<br>b. Modern-looking equipment, fixtures, and fittings, appealing facilities and materials, comfort, cleanliness, user-friendly equipment, and facilities.<br>Variety in food and beverages. operation of services at a convenient time |
| Reliability | a. Ability to perform the promised service dependably and accurately<br>b. Keeping promises, accurate and timely service, safe and secure stay |
| Responsiveness | Willingness to help customers and provide prompt service |
| Assurance | Knowledge and courtesy of employees and their ability to inspire trust and confidence |
| Empathy | Caring, individualized attention the firm provides its customers |

Comparing the two tables, it is apparent that the Tangibles dimension from table 5 is correlated with the Room, Facilities, and Surroundings dimensions. In both tables 5 and 6, the category Reliability coexists.

Table 6 HOLSERV+ Dimensions (as appeared in Xiang and Tussyadiah(2014)

| HOLSERV Dimensions | HOLSERV+ | Highest-frequency words |
|---|---|---|
| Tangibles | Room | Equipment, fixtures, and fittings in the hotel room, services available in the room Cleanliness and user-friendliness |
| | Facilities | Facilities and services available in the hotel (outside the room). Breakfast, restaurants and bars, pool, and fitness/spa facilities |
| | Surroundings | Location of the hotel, proximity to amenities, public transport, and attractions |
| Employees | Employees | General appearance and behaviour of staff. Promptness, politeness, understanding, sincere, neat, and professional employees |
| Reliability | Reliability | The willingness of staff to help guests in specific situations. The way they manage requests and complaints |

This is better presented in Table 7, which shows how HOLSERV and HOLSERV+ dimensions correlate.

| Table 7. *HOLERV and HOLSERV+ Dimensions* | |
|---|---|
| **HOLSERV** | **HOLSERV+** |
| tangibles | room, facilities, surroundings |
| reliability | reliability |
| employees | employees |

However, reading the questions of HOLSERV surveys and the explanation of categories in HOLSERV+, it is apparent that the intangible dimensions are correlated. The Intangible dimensions are Reliability, Responsiveness, Assurance, Empathy and Employees.

**FIGURE 7 SERVQUAL, HOLSERV, HOSERV+ DIMENSIONS**

**SERVQUAL**
Parasuraman, Zeithaml and Berry (1985, 1988)

- **Tangibles**
- **Reliability**
- **Responsiveness**
- **Assurance**
- **Empathy**

**HOLSERV**
Mei, Dean and White (1999)

- **Tangibles**
- **Reliability**
- **Employees**

**HOLSERV +**
Boon, Bonera and Bigi (2014)

- **Room**
- **Facilities**
- **Surroundings**
- **Reliability**
- **Employees**

## ASPECT ANNOTATION ON SCALE CATEGORIZATION

As explained in detail before, the ABSA training and annotation approach allows for the creation of a more detailed classification. In order to achieve this, the annotation scheme that has been chosen from ABSA 2016 is utilised. Specifically, in ABSA 2016, the annotated aspect had a form of UpperDimensionA#LowerDimension. By utilizing this feature instead of working with SEMEVAL's initial categorisation, we create a SERVQUAL categorisation. When it comes to both SERVQUL's and HOLSERV+ categorisation, instead of using the model's categories (six and five respectively), each category is split down to the keywords used to define the category. In this way, the researcher can study the information analyzed in more detail and upscale it to each scale's main dimensions when needed. Since we are defining more categories, we expand the table with reviews with a few more randomly chosen annotation samples. The categories are created given both SERVQUAL and HOLSERV(+) analyses.

For the annotation, we start from the SEMEVAL golden annotation system for hotels (Pontiki, M., Galanis, D., Papageorgiou, H., Manandhar, S., and Androutsopoulos, I., 2016) and customize it to fit the newly developed categorisation, which is based on the SERVQUAL and HOLSERV(+) classification. The annotated data will be the training data that will be fed to the CNN algorithm later. Two linguist experts (with linguistic studies and multi-year interpretation experience) have been asked to assess the categorisation and assign three words to each category, which will aid during the annotation process. A hospitality and tourism expert has assessed the final table once more and suggested the final correction in the model.

Two annotators carry out three trials to validate the annotation schema. For all the trials, we start from the newly assembled annotation system for accommodation. Each annotator classifies an aspect for each review, which is the noun related to the annotation, using an Excel file with filters created for the specific purpose (figure 6). Consequently, the annotator assigns an aspect category and its sentiment for each review. This means that there might be different aspects related to one or more aspect categories in a long sentence. The annotators have been asked to keep track of the problems they face during the annotation process (Almagrabi, Malibari and Mcnaught, 2018). Before proceeding to the final annotation process of annotating the SERVQUAL and HOLSERV(+) schema, and, the final schema (with the new categorisations), we consulted the three experts.

| rid | HOLSEF | HolAspect | aspect_category | aspect | polarity | review |
|---|---|---|---|---|---|---|
| 73718_1 | HOTEL | PRICES | HOTEL#PRICES | NULL | positive | Price was right |
| 73718_1 | HOTEL | PRICES | HOTEL#PRICES | NULL | positive | Pleasantly surprised at $69 night. |
| 73718_1 | EMPLOYEI | PROMPTNESS | EMPLOYEES#PROMPTNESS | Front desk | negative | Front desk was not helpful, but who cares...for $69 you get a clea |
| 73718_1 | ROOM | PRICES | ROOM#PRICES | room | positive | Front desk was not helpful, but who cares...for $69 you get a clea |
| 73718_1 | ROOM | DESIGN_FEAT | ROOM#DESIGN_FEATURES | room | positive | Front desk was not helpful, but who cares...for $69 you get a clea |
| 73718_1 | FOOD_DR | PRICES | FOOD_DRINKS#PRICES | breakfast buffet | positive | Front desk was not helpful, but who cares...for $69 you get a clea |
| 73718_1 | FOOD_DR | STYLE_OPTIO | FOOD_DRINKS#STYLE_OPTIONS | breakfast buffet | negative | Front desk was not helpful, but who cares...for $69 you get a clea |
| 73718_1 | ROOM | CLEANLINESS | ROOM#CLEANLINESS | room | positive | Front desk was not helpful, but who cares...for $69 you get a clea |
| 73718_1 | SURROUN | NEARBY_AME | SURROUNDINGS#NEARBY_AMENITIES | NULL | positive | Stayed there because it was near Banner Hospital. |
| 73718_16 | HOTEL | GENERAL | HOTEL#GENERAL | hotel | negative | Very disappointing hotel |
| 73718_16 | FACILITIES | GENERAL | FACILITIES#GENERAL | services | negative | Lots of services promised and not provided. |
| 73718_16 | SURROUN | TRANSPORT | SURROUNDINGS#TRANSPORT | shuttle | negative | The shuttle wasn't running, and the restaurant was closed down |
| 73718_16 | FACILITIES | GENERAL | FACILITIES#GENERAL | restaurant | negative | The shuttle wasn't running, and the restaurant was closed down |
| 73718_16 | | | # | | | So I guess you should make sure it's going to be busy when you g |
| 73718_16 | SURROUN | NEARBY_AME | SURROUNDINGS#NEARBY_AMENITIES | business center | negative | The business center has been taken apart - the front desk staff di |
| 73718_16 | EMPLOYEI | KNOWLEDGA | EMPLOYEES#KNOWLEDGABLE | front desk staff | negative | The business center has been taken apart - the front desk staff di |
| 73718_16 | FACILITIES | GENERAL | FACILITIES#GENERAL | Vending machines | negative | Vending machines were out of everything except in the lobby. |
| 73718_16 | EMPLOYEI | COURTEOUS | EMPLOYEES#COURTEOUS | Staff | positive | Staff was very friendly and a bit embarrassed about everything th |
| 73718_16 | ROOM | GENERAL | ROOM#GENERAL | room | positive | The room itself was fine. |

**FIGURE 8 EXCEL ANNOTATION SYSTEM**

The inconsistencies between the two annotation files are discussed with the expert linguists. Additionally, an academic expert in Tourism and Hospitality is consulted to finalize the solutions, linguists' suggestions for both the aspect categorisation and the inconsistencies on annotation.

After the annotation phase, there were categories that in the 1,083 sentences did not get any annotation or got scarce annotation in a total of 1,083 sentences (i.e., accuracy, error-free code / without_mistakes, and service_on_time, problem administration, efficiency, security, convenient operating hours). This is an indication that there might be some categories less represented, especially under the intangibles dimensions group. It also indicates that there might be a few dimensions missing when examining online reviews from a small group of accommodation units. Nevertheless, to feed the machine learning algorithm, examples from all categories need to be annotated; otherwise, the algorithm cannot be trained correctly on the dataset. Therefore, the expert linguists have been asked to provide keywords for the specific categories. These keywords were used to create sentences related to the specific dimensions.

Moreover, augmentation techniques have been manually applied to increase the training dataset and create homogeneity among the categories. Data augmentation techniques are widely used in text and visual recognition tasks to deal with scarcity and overfitting issues (Giridhara et al., 2019; Marivate and Sefara, 2019). The techniques that were manually implemented in this thesis are the substitution of words with synonyms (Jungiewicz and Smywinski-Pohl, 2019; Giridhara et al., 2019; Galinsky, Alekseev and Nikolenko, 2017), contextual augmentation, where the words are replaced with others with paradigmatic relations (Kobayashi, 2018; Xu et al., 2016), and swap of words in sentences (Wei and Zou, 2019). All in all, the 396 ABSA annotated sentences were correlated to the new categorisation and were expanded and annotated to 1,083 sentences. The augmentation process resulted in 2,121 sentences for the SERVQUAL and HOLSERV(+) model and to 2,831 relations for the enriched model, which will be presented in the next section.

Based on the aforementioned work, Table 8 presents another view of the dimensions of both SERVQUAL and HOLSERV(+) models. This approach provides three different groups of dimensions. From upper-SERVQUAL group TANGIBLES, RESPONSIVENESS, ASSURANCE, EMPATHY, RELIABILITY, to the next-HOLSERV(+) group of ROOM, FACILITIES, SURROUNDINGS, EMPLOYEES, RELIABILITY. Finally, we arrive at the lowest level group, which directly correlates to every question of the SERVQUAL scale and dimensions created from HOLSERV+ keywords, which introduced some new categories in the model.

Table 8 Aspect Categorization Based on SERVQUAL and HOLSERV+ analyses

| DIMENSIONS | RELATION | ROOM |
|---|---|---|
| TANGIBLES | V1. MODERN_LOOKING_EQUIPMENT and HOLERV+ | ROOM#DESIGN_FEATURES |
| TANGIBLES | HOLSERV+ | ROOM#CLEANLINESS |
| TANGIBLES | HOLSERV+ | ROOM#COMFORT |
| TANGIBLES | HOLSERV+ | ROOM_AMENITIES#USER_FRIENDLY |
| TANGIBLES | HOLSERV+ | ROOM_AMENITIES#EQUIPMENT |
| | | **FACILITIES** |
| TANGIBLES | V2. FACILITIES_VISUALLY_APPEALING | FACILITIES#DESIGN_FEATURES |
| TANGIBLES | HOLERV+ | FACILITIES#MISCELLANEOUS |
| | | **SURROUNDINGS** |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#LOCATION |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#NEARBY_AMENITIES |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#TRANSPORT |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#ATTRACTIONS |
| | | **EMPLOYEES** |
| TANGIBLES | V3. EMPLOYEES NEAT-APPEARING AND HOLSERV+ | SERVICE#APPEARANCE |
| TANGIBLES | V4. EMPLOYEES_NEAT-APPEARING AND CLEAN_MATERIALS AND HOLSERV+ | SERVICE#CLEANLINESS |
| RESPONSIVENESS | V10. INFORMATION_ACCURACY | RESPONSIVENESS#SCHEDULE_ACCURACY |
| RESPONSIVENESS | V11. PROMPT_SERVICE / LODG.RESP. AND HOLSERV+ | RESPONSIVENESS#PROMPTNESS |
| RESPONSIVENESS | V12. WILLING_TO_HELP | RESPONSIVENESS#EAGERNESS |
| RESPONSIVENESS | V13. NEVER BUSY TO RESPOND | RESPONSIVENESS#AT_CUSTOMERS_DISPOSAL |
| ASSURANCE | V16 CONSISTENTLY COURTEOUS EMPLOYEES TOWARDS CUSTOMERS HOLSERV+ (POLITENESS) | EMPLOYEES#COURTEOUS |

| | | |
|---|---|---|
| ASSURANCE | V17. KNOWLEDGE TO ANSWER CUSTOMER QUESTIONS/ LODG.ASSUR. | EMPLOYEES#KNOWLEDGABLE |
| EMPATHY | V18. INDIVIDUAL ATTENTION | EMPLOYEES#INDIVIDUAL ATTENTION |
| EMPATHY | V20. EMPLOYEES WHO GIVE CUSTOMERS PERSONAL ATTENTION, HOLSERV+ | EMPLOYEES#CARING |
| EMPATHY | V21. CUSTOMERS_INTEREST_AT_HEART | EMPLOYEES#CUSTOMER_CENTERED |
| EMPATHY | V22. UNDERSTAND_CUSTOMERS_SPECIAL_NEEDS AND HOLSERV+ | EMPLOYEES#UNDERSTANDING_SPECIAL_NEEDS |
| | | **RELIABILITY** |
| RELIABILITY | V5. HOTEL FULFILLS ITS PROMISES AT THE TIME THE TIME THEY HAVE SPECIFIED REL.LODG. | RELIABILITY#SERVICE_ON_TIME_WHEN PROMISED |
| RELIABILITY | V7. THE HOTEL PERFORMS THE SERVICE RIGHT AT THE FIRST TIME (EFFICIENCY, RELIABILITY) | RELIABILITY#EFFICIENCY |
| RELIABILITY | V6. PROBLEM_ADMINISTRATION and HOLSERV+ | RELIABILITY#PROBLEM_ADMINISTRATION |
| RELIABILITY | V8 KEEPS_PROMISES_ON_TIME LODG.REL. DEPENDABLE/CONSISTENT | RELIABILITY#DEPENDABLE |
| ASSURANCE | V9.ERROR_FREE_CODE | RELIABILITY#ERROR_FREE_CODE |
| ASSURANCE | V14. EMPLOYEES_INSTILLING_CONFIDENCE | RELIABILITY#INSTILLING_CONFIDENCE |
| ASSURANCE | V15 SAFETY AND SECURITY | RELIABILITY#SECURITY |
| EMPATHY | V19 CONVENIENT OPERATING HOURS | RELIABILITY#CONVENIENT_OPERATING_HOURS |

## Machine Learning Algorithm

For this research, a model of four deep neural network layers is developed, utilizing Keras libraries, an open-source neural-network library specifically designed for Python. More specifically, a sequential model has been developed, which consists of a linear stack of layers. The layers include Dense, Activation and Dropout layers. The dropout layers are used to avoid overfitting of the model by randomly setting a fraction of input units to zero at each training. To process the vast amount of extracted data, the Python environment was set on a Windows ec2 Amazon server. The nature of the deep learning convolutional neural network does not allow the possibility to be run on parallel processors, and at the same time, the available data need a significant amount of temporal memory. Therefore, the x1e.2xlarge ec2 server was chosen, which allows for 244Gb SSD memory to be utilised. The server instance was run on an Amazon German server, and all the extracted information has been taken place through German DNS servers as well.

The Convolutional Neural Network (CNN) model consists of a dense layer with 512 nodes and an input shape of 6000 words embedding layer activated by relu nonlinear activation function. The nonlinear function makes it possible to transform the information so that the resulting transformed data can be classified into different classes.

Subsequently, a dropout layer to prevent overfitting and reduce the size, and a dense layer with nodes were activated with ReLu activation function. Finally, the output layer comprised 31/57 neurons (31 in the initial model and 57 neurons at the final proposed model), one for each category, through a dense layer activated with sigmoid function. This makes it possible to achieve probability distribution among the 31/57 classes that we want to predict in the enhanced model. Softmax, sigmoid activations were both tested, but sigmoid returned the best results. The training and extraction of the multi-class model are based on the binary cross-entropy classifier. The model is trained with the aforementioned pre-labelled dataset.

The Bag of Words word embedding technique has been used to encode the review sentences in vectors, creating a high dimensional vector space. In this matrix, each vector is a one-hot encoded representation for each sentence's tokenized words (dimension 6000x – reviews tokenized), which have been sorted based on their frequency.

Moreover, the aspect categories are encoded to a binary variable (dummy variable) before fitted to the test dataset. Eleven epochs at a batch size of 64 samples is the chosen fitting process for the model, to avoid overfitting while reaching optimal results. Additionally, the model is run with Adam optimizer. The learning rate, as its name implies, specifies the learning rate of the deep neural model during the training process. For this model, the trials showed that it achieves optimal results at a constant learning rate of 0,01. This model returned more than 74 % accuracy, which is a satisfactory result for the model.

## MODEL VALIDATION AND EVALUATION

### *CROSS-VALIDATION*

Cross-validation is the technique where the training dataset is partitioned into a training dataset that is used to train the model and an independent dataset which evaluates the analysis. Additionally, as presented in the following figure, k-fold cross-validation has been chosen in order to minimize the variance of the model's estimated accuracy. This technique takes place before the analysis stage hence, it gives information about the possibility of overfitting and the level of generalization of the model on independent data. In other words, the purpose of the trained model is to perform well on unseen information. The generalization of the training data into the test data will ensure the trustworthiness of the Convolutional Neural Network Model. In order to validate, the training data are split into two datasets. 90% of the initial training data are fed to the model in order to train it, and the remaining 10% per cent acts as the test data. The predicted values of the test data are cross-validated to the actual values of the initial training data. The result gives an estimation of the validity of the model. The aforementioned compiled model performed well, returning 71.69% F1-measure accuracy.

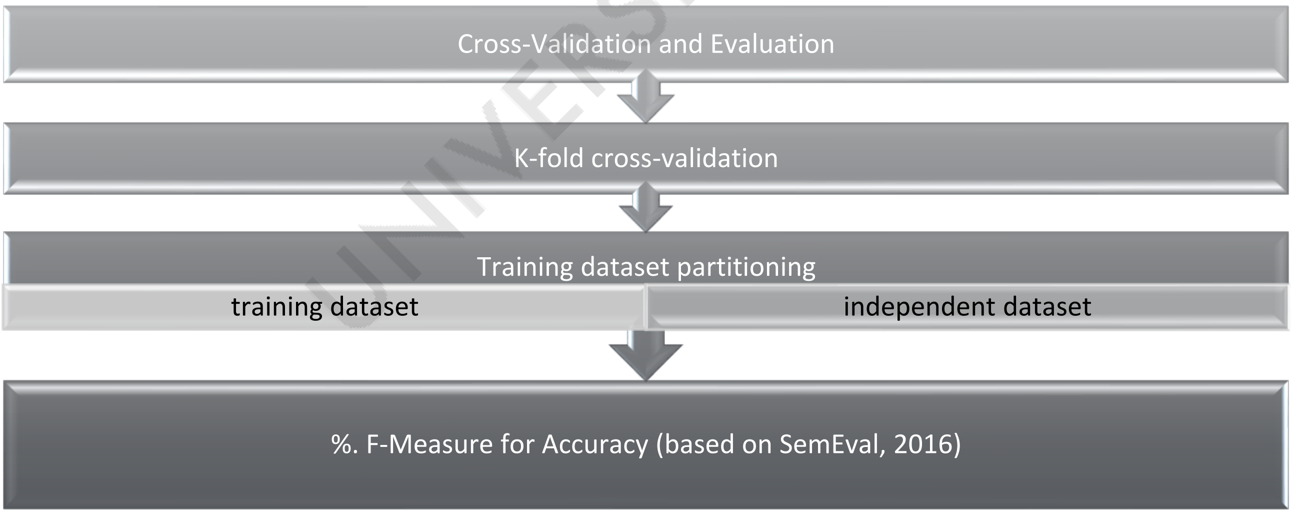



**FIGURE 9 CROSS VALIDATION**

F-Measure (also F1 score) is a measurement that considers both precision and recall measures. F-measure is the harmonic mean of precision and recall values for the classification problem, where F-measure reaches its highest (best) value at 1 and its lowest (worst) value at 0.

$$F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

***MODEL EVALUATION***

For the model evaluation, two more metrics are used to quantify model performance.

***PRECISION***

Precision is a measurement that specifies what fraction of the model's prediction output is accurate, compared to the human annotators' output. Precision is the number of correctly labelled annotations (correct positive results) divided by the total predicted annotations (total predictive positive) created by the neural model.

precision = Total Positive / (Total Positive + False Positive)

A low precision score (tending to 0) means that the machine-learning algorithm produced incorrect annotation, whereas a precision value of 1.0 means that every labelled case is correct. The Precision measure does not provide information related to how many other labelled cases for a specific class were missed by the algorithm. This information can be provided from the recall measure.

The Recall (or True Positive Rate or Sensitivity) measure returns how many sentences that should have been annotated with a specific category have actually been annotated correctly. Recall score, therefore, gives the number of positive/correct annotations out of the total positive labelled annotations. A value of 1 means that every annotation has been correctly annotated, while a value of 0 means that none of the labelled annotations have been labelled correctly.

recall = Total Positive / (Total Positive + False Negative)

#### *LOGARITHMIC LOSS*

Logarithmic loss (logloss) measure shows the classification model's performance by measuring the negative average of the log of corrected predicted probabilities for each case. Log loss values express probabilities, and therefore, its values range from 0 to 1. When the probability diverges from the actual category, the log value tends towards 1.0. Consequently, the logloss value decreases when the predicted probability gets closer to the actual label. Therefore, the classification algorithm's goal is to reach a low logloss value.

$$-\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

where:

p(yi) is predicted probability of positive class

1-p(yi) is predicted probability of negative class

yi = 1 for positive class and 0 for negative class (actual values)

The evaluation of the model follows the evaluation method of SemEval 2014 (Pontiki, M., & Pavlopoulos, J. (2014)), where the F-measure has been chosen as the evaluation metric. Moreover, the Logarithmic Loss and Precision and Recall measures are presented.

## 3.7 CONCLUSION

In the third Chapter the Research context has been set, providing the Research Aim and Research Questions as well as the Methodological Approaches for both studies. The first study is investigating the perceptions of accommodation managers on online reviews in comparison to traditional surveys. The second phase analyses the extracted reviews based on the initial multi-level categorization model. The multi-dimensional model makes it possible to research how well online reviews can fit SERVQUAL and then HOLSERV and HOLSERV+ models. The last part of the study researches the possibility of enhancing the model with categorisations that improve the model's explanatory power. After developing the final proposed multi-dimensional model, the online review corpus is fitted to the model and a discussion on the results and findings follows.

# CHAPTER 4. RESEARCH FINDINGS AND DISCUSSION

## 4.1 INTRODUCTION

This Chapter presents the two methodologies and the practical parts of the thesis. As already mentioned before, Crete's case has been chosen for both studies, due to the significance of the tourism industry in the country's economy and the differentiated tourism groups (cultural, sightseeing, business, leisure, agrotourism) that visit the country through the year.

First, the Thesis proceeds to the email interviews from Managers of Hotels in the region of Crete. As discussed in the second Chapter, researchers have been studying online reviews and quality assessment surveys separately (Lai et al., 2018). To the author's knowledge, a study is yet to provide information on how hotel managers perceive the information obtained from these two tools. This study researches how hotel managers perceive these two tools. It also investigates the usefulness of online reviews for hotel managers. Moreover, the Thesis researches how the information gained from questionnaires is related to online reviews (i.e. if hoteliers believe that one of these tools provides different information or if they provide overlapping information). Initially, this Section discusses the results concerning the managers' chosen quality assessment method. Then, it provides their views on information completeness based on each assessment method. Also, the study provides the participants' opinions regarding the comparison of the two assessment approaches. The discussion moves towards the efficiency of the tools and their profitability. Each tool might have different grades of efficiency when it comes to quality evaluation, but also, they might cover specific needs based on the views of each manager, as well as affect the profitability of the business in a variety of ways. Later, the participants' sense concerning each of these tools' reliability and quality is discussed before viewing the ease of adapting each method for their businesses. Finally, the Thesis gives the accommodation providers perception on the future of assessment tools and their needs that remain to be covered.

The next Section provides the results and findings from the second study, where the data from the online reviews are extracted, analyzed, and synthesized, reaching the present Thesis conclusions. The first part of this Section provides the validation and evaluation results of the convolutional neural network classification algorithm application for the initial multi-dimensional model that includes the SERVQUAL and HOLSERV(+) classification on the online reviews corpus. Then the Thesis presents the results of this classification method, also providing an analysis of the categorisations extracted. A heat map has been applied to the categories' frequency to facilitate the reader in all the tables that follow. Also, colour coding allows for easier identification of each dimension. Next, the descriptive analysis is presented, where the results are discussed, focusing mainly on the emerging dimensions that are not represented by the previous models. The next part of the Section presents the Analysis on the Enriched Quality Assessment Model, the resulting tables and provides a discussion on the results. In the next Chapter Conclusions and Results for both studies are presented.

## 4.2. RESEARCH RESULTS ON MANAGERS' PERSPECTIVES STUDY

In this section, the email interviews results are presented, discussed, and connected with the knowledge provided from existing literature on the subject.

### 4.2.1 PARTICIPANTS' CHOSEN ASSESSMENT METHOD

Every hotel in our sample uses online reviews to extract useful information and to assess their service quality. Most hoteliers (8) use both questionnaires and online reviews, while the remainder only use online reviews. The most popular online review provider is TripAdvisor (12) with Booking.com (11) in the second place. Other providers are Google, Expedia, Airbnb, Facebook, and HolidayCheck. Moreover, two hotels use commercial solutions like ReviewPro and Reviewer. One case also takes into consideration tour operators' insight on the quality provided. Finally, another hotel manager uses his daily relations with customers to stay up to date regarding the quality of the services they enjoy.

E.R. hotel uses both surveys and online reviews and considers online reviews to have better quality and be more honest. K.R. hotel share the same notion of quality, because customers can review the quality they receive at any point during their stay, which makes it possible to offer them an immediate solution to their problem. Ac. and G.C.S. hotels argue that usually, online reviews take place after the customers have left the hotel, and they have the composure to do an objective assessment of their stay.

### 4.2.2 Assessment Method and Information Completeness

Generally, six participants found online reviews to give more complete information than questionnaires; four people found that questionnaires provide more thorough information, and another four participants thought the combination of the two tools provides the most complete information (Fig. 10).

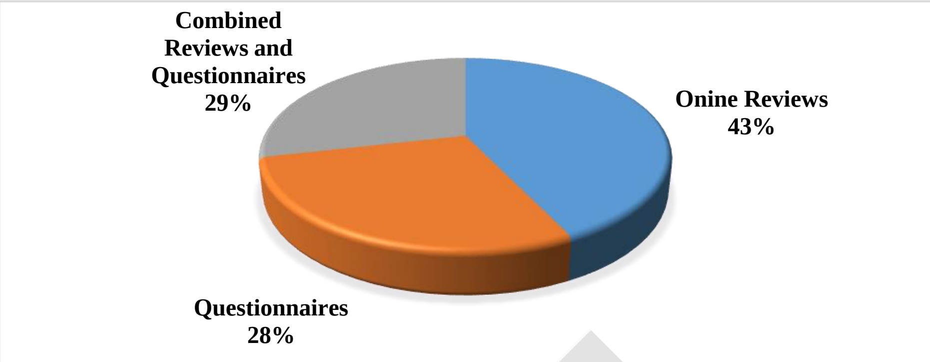



FIGURE 10 PERCEPTION OF COMPLETENESS OF INFORMATION

K.R. notes that online reviews provide complete information because they can be given in various phases multiple times by the same customer (editing and building in their first impression). They are also considered to focus more on the customer services that need to be improved (G.C.S., S.M.N.).

A few of the participants find that questionnaires to provide more information mainly because they are oriented towards the company’s goals (H.B., Ap., S.M.N.). Additionally, R.C.V. finds that “questionnaires provide a larger source of information, based on the variety of topics discussed”.

To sum up, questionnaires provide a variety of different topics while reviews need to be very analytical to cover them. Furthermore, questionnaires aid in developing targeted questions based on the quality goals of the company. On the other hand, online reviews offer customers the possibility to continuously evaluate their stay, which gives hoteliers the opportunity to keep customers pleased while solving their problems as they appear. The same is true for unstructured online reviews. They provide hotels with the assessment of subjects and services they might not have thought about before.

### 4.2.3 Online Reviews versus Traditional survey

When it comes to the differences between these two tools, there was one case where the respondent could not identify any differences (C.B.C.R.S.). E.R. points out that “the further analytical an approach can be, the more useful the results and decisions the administration will take”. When they are well structured and targeted, however, they have the same weight for the administration (E.R.). Of course, there are respondents that have noticed advantages and disadvantages to each tool and might have shown their preference to one or the other.

The majority of the respondents (11) recognize some advantages, and a few express their preference towards surveys (2). Specifically, “their questions are more straight to the point” (O.P.R.), and these “questions can also be targeted based on the hotel’s goals” (H.B.). According to G.C.S., “surveys analysis is easier due to closed-ended and multiple-choice questions.” R.C.V. mentions that “Older people generally prefer service quality assessment scales to online reviews.” R.C.V. also prefer questionnaires because online reviews usually take place a while after the stay, in comparison to surveys that take place while the customer is in the hotel (S.B.C.R.S.). This means that the memory of the customers’ experience has fainted (Id.) Moreover Id. explains that there are requirements to be met when it comes to questionnaires; for instance, “need to be easily comprehensible and enjoyable to fill out”.

Other respondents (10) prefer online reviews. Ag., G.C.S. K.R. representatives believe that online reviews are more objective than service quality assessment scales, while K.R. also considers that the ability in online reviews to have further contact with customers based on their review is crucial. Furthermore they claim that, “customers can review the hotel online and then edit their review as many times as they like, which creates a real-time relation between customers and hotel managers” (K.R.). Also, “online comments are better targeted to positive or negative aspects based on customer experience, which makes them more realistic than surveys” (G.C.S.). From the hotelier’s point of view, online review platforms allow for easier access and search on customers’ assessment. “Through positive online reviews, hotels attract customers” (G.C.S.). They are faster to complete and more enjoyable (Id.)

Summarizing this information, one can argue that survey analysis might be easier due to their format (close-ended and multiple-choice questions). Additionally, older people tend to prefer service quality assessment scales to online reviews. The only inconvenience surveys present is in preparing a carefully planned, goal-oriented and fun questionnaire (Id.Hotel).

On the other hand, respondents embrace technological advancements and online reviews. Online comments are given in real-time, and offer the possibility (when they take place during the stay) for customers to continuously evaluate their stay, which allows hoteliers to keep customers pleased while solving their problems as they appear. The same is true of unstructured online reviews; they provide hotels with an assessment on subjects and services they might not have thought about before. McAfee and Brynjolfsson (2012) mention that it is difficult to extract knowledge from vast sources of information (McAfee and Brynjolfsson, 2012), but according to this survey's respondents, commercial tools that have been developed and are available online overcome this problem (O.P.R., R.C.V.).

### 4.2.4 Needs Covered, Profitability and Efficiency

Questionnaires are admittedly aiding in improving the quality of services and assessing employees' work (E.R.). Furthermore, if the hotel manager takes the time to review and analyze the questionnaires every couple of months, "questionnaires help in capturing in-season problems and fix them" (E.R.). Additionally, questionnaires can be "customized on the quality goals of the hotel" (R.C.V.). When the survey is provided at the hotel reception during the visitor's stay, they might offer the opportunity to discuss possible problems with the client (S.B.C.R.S).

Online reviews, on the other hand, provide instant feedback and the opportunity for hoteliers to respond in-time and solve the problem (E.R.). "They measure the guest satisfaction and how clients perceive the service quality and the establishments they enjoy, in comparison to competitors and their past experiences" (O.P.R.). Online reviews can help improve and correct mistakes, omissions, services, and staff (Id.). "They can be more helpful than questionnaires because they include information that is not asked in surveys" (O.P.R.). Online reviews, in addition to for improving the service quality provided, "they aid in achieving better contracts with tour operators" (K.R.). As a marketing tool (R.C.V.), they improve the hotel's image and presence in the Hospitality market (Id.), aiding in attracting more customers (G.C.S.)

Most of the survey participants (9) state that both tools aid in improving service quality provided to customers. They are vital in order to keep a tourism company competitive (Id.).

Efficiency plays a significant role in hotel management either as a synchronous or asynchronous response or in a resource-consuming base. In this aspect, the findings are consistent with Gretzel et al. (2010), who state that online reviews can be assessed in real-time, making the hotel's reputation management system more effective. Furthermore, the results show that online reviews offer the possibility to have real-time updates on the customers' experience (Em.Ap.), find information easily (K.R.), understand tendencies, assess service quality, and keep in contact with the travellers and respond in-time to their comments. Additionally, since the main difficulties of adapting to online reviews are related to time management and response time (Ac., Ap.), the respondents point out that these issues can be alleviated by employing commercial tools (O.P.R., R.C.V.). These findings comply with Li, Ye and Law (2013), who state that hotels can achieve a reliable systematized assessment of service quality systems by utilising these new technologies and methodologies. In support of the aforementioned S.B.C.R.S. hotel suggests that travellers nowadays leave and read online reviews, so adapting and managing this new tool properly is vital for the company's sustainability.

Another way to understand the needs that each tool covers for hotels is how they affect the revenues and, subsequently, profits of the company. Profitability is an important index affecting the vitality and sustainability of the company. Our respondents mention a few different channels through which online reviews and service quality assessment scales affect the company's profitability. Through quality assessment tools, they develop a better understanding of their business's advantages and disadvantages, and as long as they work on the negative remarks and sustain and improve the positive ones, they achieve mid- and long-term rising profitability. Marketing and advertisement is the second primary profitability channel mentioned by the survey participants. K.R.'s respondent has noticed the quality assessment aids in improving the services provided, which leads to returning customers. Also, a few participants (5) mention that improving their services creates a positive image and a positive word of mouth around their name. S.M.N. explains that "if a customer is satisfied, they will suggest our hotel to others as well". A few (3) have pointed out the additional advantage of online reviews, which create an electronic word of mouth accessible to many more possible customers than just the traditional word of mouth advertisement. O.P.S.R.'s sales manager points out that "when their online reviews and ratings improve, this improves the positive image of the company, resulting in achieving higher prices in the next season and thus greater profits". Additionally, E.A. has noticed that "better ratings are linked to better sales". G.C.S. mentions that online reviews "can act as means of protecting the hotelier from bad employees and services and therefore have a great impact on their long-term profitability". Finally, O.P.R. points out that improved online ratings, in addition to for having a positive impact on next season's prices, they also provide more choices of collaboration with tour operators. Also, additional ratings are a powerful negotiation tool on prices achieved when discussing with the tour operators.

Profitability, as mentioned, is well-linked with both assessment tools. Both tools give the customers' point of view on their services and products. Improving their services leads to returning customers and positive word of mouth. Online reviews provide the electronic word of mouth advertisement reaching many more possible customers, and therefore, they contribute to raising the prices either in response to higher demand from online customers or by negotiating better prices with tour operators.

### 4.2.5 Adaptability, Reliability, and Quality

Regarding the adaptability of online reviews, four participants found them easy to adapt since Ac. Hotel owner clarifies, "you just need to follow the easy and clear guiding lines of each site". Some hotels have faced some difficulties concerning the adaptability of online reviews. O.P.R. hotel suggests that "a big sample is needed to study the trends and assess quality". S.M.N., H.B. and K.P. hotels mention that the hotel needs a proper promotion in order to incentive customers review their stay and then the hotel staff has to categorize the reviews, assess the results, and save them. Referring to the time that is needed in order to process online reviews, Ap. Hotel adds that "even more time is needed in order to respond to the comments left by customers". For them, analyzing and responding to online reviews adds an extra task to their already busy schedule.

The reliability of online reviews is a subject of concern for hoteliers as well. The majority of the hotels suggest that surveys are more reliable and useful when they are adequately prepared and correctly targeted because they provide knowledge based on the hotel's informational needs. One-third of the respondents trust online reviews, and another third believes that both surveys and online reviews are equally reliable tools. Only one participant (Agr.) believes that they cannot be trusted, while three hotels do not use traditional surveys.

Id. Hotel's representative again suggests that the quality of Surveys is better because online review takes place a while after the visit, which means that the memory of the quality of services provided has fainted. Ag. works with both tools, but they believe that although reviews are inconsistent, their information is more objective. Moreover, S.M.N. considers online reviews to be arbitrarily structured based on the customer's experience, while questionnaires to be structured, providing consistent information. Additionally, the Id. Hotel representative has noticed that when people complete surveys during their stay at the hotel, clients have a fresh memory of the product they evaluate. O.P.R., R.C.V. and Ac. hotel informs us that when surveys are appropriately developed, they are a better source of information since the results they provide are exactly what the hotel needs to analyze. E.R. hotel mentions that online reviews can be untrue, and the participant might not had personal experience of the hotel. In the same vein, Id., Ac., E.R. and R.C.V hotels suggest that online reviews should be crosschecked in order to ensure their reliability. Finally, Ac. representative argues that "hotels should be prepared to make quick adjustments based on negative comments they might receive from online reviews". "Although online reviews can offer a lot of important information, they need to be classified and analyzed before the manager can make useful inferences" (R.C.V.). Besides this, "online reviews fail to offer feedback on some of the less visited departments of the hotels" (R.C.V.)

Although there are different views on when the quality assessment should take place (during the stay or later) opinions on which tool provides more reliability and quality of information vary. The main indisputable argument for surveys is that they provide structured information oriented toward the hotel's assessment needs.

### 4.2.6 ACTIONS TAKEN

In this section, we discuss the actions taken by the participants concerning problems or weaknesses that have been introduced by surveys or online reviews.

Most of the participants (12) in this study have taken actions towards improving their facilities, room, and staff services. A lot of the improvements pertain to the cleanliness of rooms and facilities. Furthermore, a few are related to services like after midnight service, ways of check-in, or restaurant menu). One participant, H.B. hotel also mentions that these tools help them create targeted advertisement campaigns.

Quality assessment questionnaires are developed with the evaluation of quality in mind, so they measure specific dimensions of service quality. Online reviews however, provide unstructured information on travellers' experiences, so it is interesting to explore if they provide information on similar dimensions to that provided by service quality assessment scales. The actions hotels have taken based on online reviews can provide us with insight into this aspect. Advocating for online reviews, Berezina et al. (2016) remark that online reviews support the basic structure of service quality scales, which separate tangible (i.e., room furnishing) from intangible (i.e., staff services) aspects. To explore the statements mentioned above, we can compare the response from online reviews and questionnaires in relation to a scale that can connect both of them. HOLSERV measurement scale is a tool that was developed based on the SERVQUAL scale. In the absence of online review scales, Boon, Bonera and Bigi (2013) developed the HOLSERV+ scale based on the HOLSERV dimensions and targeted specifically in retrieving service quality information from online comments. This tool can aid in evaluating this survey answers between respondents that use online reviews only for assessment purposes and those that use both tools. HOLSERV+ has five dimensions of service quality assessment. These dimensions are Room, Facilities, Surroundings, Employees, Reliability.

With the HOLSERV+ scale which in mind, as mentioned before, provides a safe connection between traditional Hospitality questionnaires HOLSERV and online reviews, we can observe that from the seven respondents that use solely online reviews as service quality tools, four participants mentioned actions they have taken towards room facilities and services, four mentioned improvements in Facilities and services outside the room (pool, breakfast hours), one mentioned actions related to Employees and one mentioned reliability improvements. In our sample, we had no respondents that use solely online reviews to refer to actions taken towards Surrounds, whether they are in relation to the location of the hotel, the proximity to amenities, attractions, or public transport.

On the other hand, from the eight participants that use both traditional surveys and online reviews, the results are different. Only one participant mentioned the Room dimension while we had nine mentions regarding actions taken in improving the Facilities dimension. One action is related to each of the dimensions of Surroundings, Employees, and Reliability. One participant, R.C.V., also added two actions that were suggested in online comments, which are related to Facilities (ways of check-in, improvement of a dish in the restaurant).

### 4.2.7 Future of Assessment Tools

As mentioned previously, eight of the respondents use both questionnaires and online reviews. Also, almost half of them use only online reviews, while two combine them with face-to-face discussion with clients or receive feedback from the tour operators regarding their service quality.

E.R. hotel argues that it is still relatively challenging only to use online reviews. This is due to the fact that many customers prefer service quality assessment scales and do not want to spend additional time reviewing the service quality after they have left the hotel establishments. S.M.N.'s proprietor explains that "customers are more eager to fill the questionnaire at the hotel as soon as it is given to them, while only 10% of them provide online reviews after they have left the hotel". H.B. and S.B.C.R.S hotels argue that online reviews require the collaboration with specific channels that take control of assessment from the hands of the hotelier. R.C.V. hotel mentions that "online reviews fall short on information provided while, they can extract more information through service quality assessment scales".

On the other hand, K.R.'s representative considers surveys "outdated, and in need of replacement". Specifically, he explains, "questionnaires are filled out either the moment the customers leave the hotel or after they have left, which makes it, in most cases, impossible to give solutions to their problems". "Online reviews", he continues, "provide the possibility to review the hotel while staying there, and therefore give the opportunity to the hotel management to take better care of the customers, by giving in-time solutions to their problems". Ag. believe that having more customers reviewing online, could gradually lead them to replace service quality assessment scales with online reviews.

Most of the respondents (9) believe that both service quality assessment scales and online reviews are necessary. H.B.'s general manager goes one step further, adding that both tools will be available in the future. What changes is that technology supports new ways of accessing these tools and reporting results.

### 4.2.8 Discussion

The first study has aimed to investigate the opinions of hoteliers and hotel managers in Crete regarding service quality assessment scales and online reviews as quality assessment methods. This study adds to the field on issues that have been pointed out by existing literature. Researchers underlined the necessity to research the role that online reviews play within organisations regarding their service quality assessment system (Li, Ye and Law, 2013; Duan et al., 2013).

Xiang and Gretzel's (2010) statement that hotel managers increasingly use travel review platforms for their market research strategies is supported by the study's findings, where all respondents use online reviews to extract useful information. Moreover, eight out of fifteen respondents employ both service quality assessment scales and online reviews when assessing service quality. Specifically, as a marketing tool, online reviews improve the hotel's image and presence in the Hospitality market, aiding in attracting more customers. Finally, online reviews are accessed by tour operators and potential customers, improving the company's overall image, allowing hoteliers to achieve better prices in the next season and attract more customers.

Among the findings of the research is that most participants of the study have been using TripAdvisor for viewing, analyzing, and responding to online reviews. The second most used Travel Portal is Booking.com. Participants, however, are divided when it comes to which tool or combination provides more complete information. More research can be done in this direction by studying online reviews in relation to the questionnaires' quality dimensions.

Researching completeness, informational needs, and the possibility of overlapping information a few more benefits and weaknesses of these two tools come to light. Among the advantages of online reviews is that when travellers evaluate hotel services during their visit, hotel management has the chance to respond and provide solutions to problems. In this way, customers can have a more pleasant stay and businessmen achieve better ratings and reputation, which is also consistent with the findings of Gretzel et al. (2010). Consequently, it might be beneficial for every party if tourism stakeholders encouraged travellers to give their evaluations concurrently with their experiences.

Moreover, online reviews give the possibility to hoteliers to further contact visitors concerning their comments. This is also consistent with Li, Ye and Law (2013), who state that since customer reviews are based on open-ended questions (versus the fixed questions of quality surveys), they might provide additional service quality information that service quality assessment scales do not cover. Furthermore, online reviews can provide hotels with an assessment of subjects and services they might not have thought of. According to the respondents, the weakness of online reviews mentioned by McAfee and Brynjolfsson (2012) seems to have been overcome with the aid of commercial tools.

On the other hand, hoteliers find it easier to analyze questionnaires because they consist of close-ended and multiple-choice questions. Questionnaires provide a wide range of topics while reviews need to be very detailed to cover all possible topics. Furthermore, questionnaires can be customized to provide information on each hotel's specific quality goals aiding in the process of evaluating their known weaknesses and toward their improvement. These findings lead us to infer that there are unique aspects of each tool that do not overlap with the other.

Also, following Sanliöz Özgen, Kozak and John Bowen's (2015) suggestion to research in additional locations (geographically) on online review trustworthiness and effectiveness regarding service quality assessment, this study adds to the existing literature by investigating the phenomenon through interviewing Greek hoteliers and managers. The results are consistent with Sanliöz Özgen, Kozak and John Bowen (2015), who find them to be reliable and effective tools in quality assessment, adding that any reliability issues can be overcome by crosschecking the reviews.

Duan et al. (2013), have pointed out the need to comprehend the impact that online reviews have on hotels' service quality actions and strategies. This impact is apparent through the actions that participants have taken towards the improvement of their service quality.  We can see a few trends that can be investigated in more detail. For instance, those that use only online reviews mentioned mostly room improvements, whereas those that use both tools mentioned mostly improvements in their facilities. Besides, we had no mention of improvements in surroundings when it comes to online reviews only respondents. That might mean that when people review accommodation online, they might not think that the hotel can affect the quality of their stay that is related to surroundings (i.e., transport, services provided by affiliated companies).

Studying the actions taken based on their quality assessment results, the study investigates the questionnaire quality dimensions found in online reviews. From the five-quality dimensions provided by the HOLSERV+ scale, the respondents seem to have realized actions on four of them, that is, Room, Facilities, Employees and Reliability. The respondents did not mention any actions taken towards the Surroundings dimension and there was only one instance out of nine mentioning the dimension Room. Although this might be a result of the low sample of the qualitative research, it might be of interest for a future research to investigate this finding further since it might lead to useful inferences concerning both tools.

Based on the findings of this research, we understand that both tools add to the quality assessment. This is consistent with the concluding remarks of Boon, Bonera and Bigi (2013), that traditional service quality tools cannot be replaced by online reviews, but hotels should combine both tools, in order to achieve abetter understanding regarding service quality. Both tools are useful and will be available in the future; what changes is that technology supports new ways of accessing these tools and reporting results. Finally, online comments by customers focus on problems that matter most to them while questionnaires serve hoteliers in assessing problems and setting quality goals that matter most to them.

## 4.3 DATA MINING: RESEARCH FINDINGS AND DISCUSSION

### 4.3.1 ANALYSIS OF THE SERVQUAL AND HOLSERV(+) MODELS

#### CROSS-VALIDATION AND MODEL EVALUATION

Cross-validation is the technique whereby the training dataset is partitioned into a training dataset that is used to train the model, and an independent dataset which evaluates the analysis. In order to validate the training data are split into two datasets. 90% of the initial training data are fed to the model in order to train it, and the remaining 10% per cent acts as the test data. The predicted values of the test data are cross-validated to the actual values of the initial training data. The result gives an estimation of the validity of the model. The aforementioned compiled model performed well, returning 77.77% F1-measure accuracy.

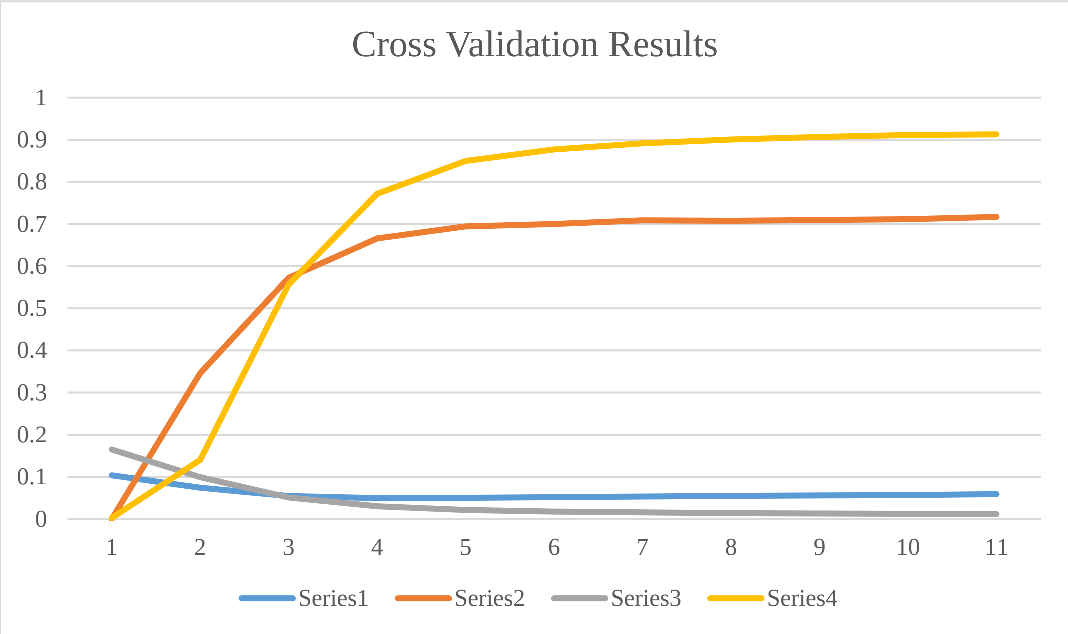


FIGURE 11 CROSS-VALIDATION RESULTS

For the model evaluation, two more metrics are used to quantify model performance.

The evaluation of the model follows the evaluation method of SemEval 2014 (Pontiki and Pavlopoulos, 2014), where the F-measure has been chosen as the evaluation metric. Moreover, the Logarithmic Loss and Precision and Recall measures are presented.

Table 9 Accuracy Metrics

| | logloss | F1 | Precision | Recall |
|---|---|---|---|---|
| 0 | 0.226694 | 0.002258 | 0.0018914 | 0.015073 |
| 1 | 0.120724 | 0.010901 | 0.2011305 | 0.005652 |
| 2 | 0.076758 | 0.267341 | 0.7663136 | 0.17334 |
| 3 | 0.043311 | 0.659034 | 0.847535 | 0.542628 |
| 4 | 0.029563 | 0.794969 | 0.8711524 | 0.731983 |
| 5 | 0.023117 | 0.841076 | 0.8920392 | 0.796985 |
| 6 | 0.019013 | 0.870589 | 0.8978808 | 0.845502 |
| 7 | 0.017711 | 0.87842 | 0.9022317 | 0.856806 |
| 8 | 0.014793 | 0.890967 | 0.9066725 | 0.876119 |
| 9 | 0.014439 | 0.892814 | 0.9062817 | 0.880358 |
| 10 | 0.012959 | 0.898752 | 0.9109099 | 0.887423 |

| | | | | |
|---|---|---|---|---|
| 11 | 0.012735 | 0.897628 | 0.9132834 | 0.883184 |
| 12 | 0.012357 | 0.902147 | 0.9133322 | 0.891663 |
| 13 | 0.012476 | 0.900548 | 0.9111064 | 0.890721 |
| 14 | 0.011679 | 0.909104 | 0.9206406 | 0.898257 |
| 15 | 0.011106 | 0.911893 | 0.9235083 | 0.901083 |
| 16 | 0.012672 | 0.902663 | 0.9139768 | 0.892134 |
| 17 | 0.011322 | 0.910492 | 0.9196112 | 0.902025 |
| 18 | 0.011469 | 0.911393 | 0.9223848 | 0.901083 |
| 19 | 0.011794 | 0.904077 | 0.9160626 | 0.893076 |
| 20 | 0.011748 | 0.903453 | 0.9165756 | 0.891192 |
| 21 | 0.010735 | 0.907484 | 0.9153707 | 0.900141 |
| 22 | 0.010732 | 0.909584 | 0.9242544 | 0.895902 |

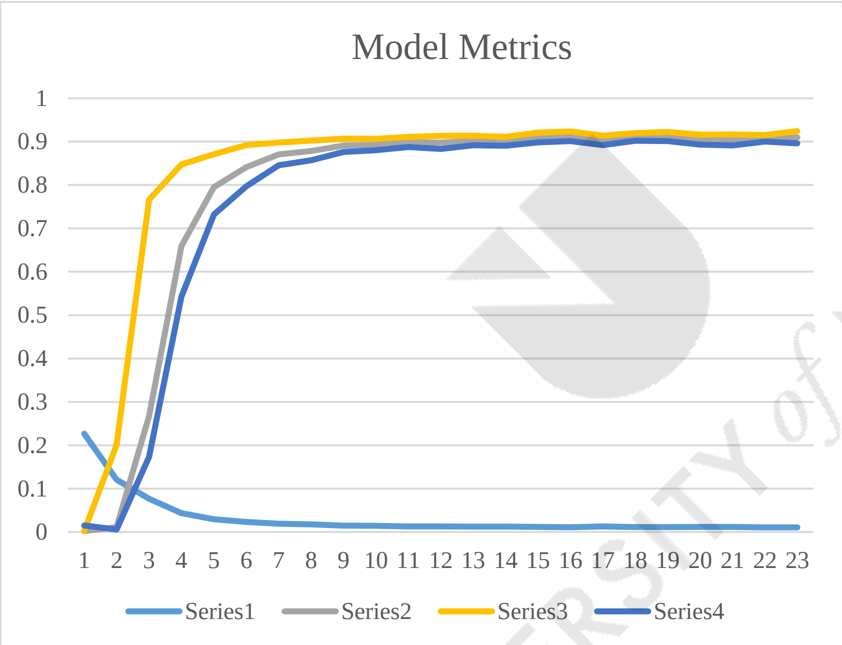



**FIGURE 12 MODEL METRICS**

The deep neural network algorithm produced class categorisation for the SERVQUAL and HOLSERV(+) models by matching 613,790 sentences to the dimensions provided by the python script run.

The aspect-based classification algorithm combined with the annotation approach of SEMEVAL 2016 and the Pre-Annotated Training Corpus developed in the previous steps, the thesis achieved in fitting the online reviews in the scales' aspects.

As presented in the previous sections, the initial multi-dimensional model created makes it possible to have a classification into the sentence-level categorization of service quality scales. Except from managing to fit the reviews in dimensions and sub-dimensions, the thesis creates mid-level dimensions that explain further the reviewers' experiences, which have also made it possible to combine the approaches of SERVQUAL, HOLSERV and HOLSERV+ studies.

As explained earlier, the deep neural network code has been run for both SERVQUAL and HOLSERV(+) dimensions. In every table, the columns for frequency and percentages have been colour-annotated with a heatmap style from dark blue (representing the highest values) to dark red (representing the lowest values) in each case.

Followingly Table 10. presents only the results for the SERVQUAL scale. The thesis moves one step further through the next tables by creating a novel way of presenting the scales' dimensions and sub-dimensions. More specifically, the table shows how the SERVQUAL upper-level dimensions can be matched to online reviews. Also, the table shows which of the SERVQUAL sentence-based aspects (lower-level dimensions) are provided in the third column. In other words, the thesis has managed to classify in scale-sentence-level in detail the aspects discussed by online reviewers when they are given only open-ended questions like "How was your stay in the X hotel?".

Specifically, in Table 10, the top five classes are FACILITIES#DESIGN_FEATURES, which is related to the TANGIBLES dimension and has 54,150. FACILITIES#DESIGN_FEATURES is 8.82% of the total amount of sentences annotated.

EMPLOYEES#CUSTOMER_CENTERED, is related to the EMPATHY dimension of HOLSERV with 37,073 counts. Moreover, EMPLOYEES#COURTEOUS from the ASSURANCE dimensions with 33,556 frequency, ROOM#DESIGN_FEATURES from TANGIBLES with a frequency of 31,790 and RELIABILITY#DEPENDABLE: RELIABILITY with 24,825 counts.

The lowest count has been from the EMPLOYEES#SCHEDULE_ACCURACY, EMPLOYEES#CARING, EMPLOYEES#INDIVIDUAL ATTENTION categories with 1,118, 916 and, 75 counts, respectively. In the SERVQUAL table, there are ten categories that have under 5,500 counts, or in other words, they are under 1% of the total annotated sentences.

| Table 10 SERVQUAL | | | |
|---|---|---|---|
| TANGIBLES | V1. MODERN_LOOKING_EQUIPMENT and HOLSERV(+) | ROOM#DESIGN_FEATURES | 31790 |
| TANGIBLES | V2. FACILITIES_VISUALLY_APPEALING | FACILITIES#DESIGN_FEATURES | 54150 |
| TANGIBLES | V3. EMPLOYEES NEAT-APPEARING AND HOLSERV(+) | EMPLOYEES#APPEARANCE | 1977 |
| TANGIBLES | V4. EMPLOYEES_NEAT-APPEARING AND CLEAN_MATERIALS AND HOLSERV(+) | SERVICE#CLEANLINESS | 2689 |
| RESPONSIVENESS | V10. INFORMATION_ACCURACY | EMPLOYEES#SCHEDULE_ACCURACY | 1118 |
| RESPONSIVENESS | V11. PROMPT_SERVICE / LODG.RESP. AND HOLSERV(+) (EMPLOYEES) | EMPLOYEES#PROMPTNESS | 7359 |
| RESPONSIVENESS | V12. WILLING_TO_HELP, HOLSERV(+) | EMPLOYEES#EAGERNESS | 3844 |
| RESPONSIVENESS | V13. NEVER BUSY TO RESPOND | EMPLOYEES#AT_CUSTOMERS_DISPO SAL | 1647 |
| ASSURANCE | V16 CONSISTENTLY COURTEOUS EMPLOYEES TOWARDS CUSTOMERS HOLSERV(+) (POLITENESS) | EMPLOYEES#COURTEOUS | 33556 |
| ASSURANCE | V17. KNOWLEDGE TO ANSWER CUSTOMER QUESTIONS/ LODG.ASSUR. | EMPLOYEES#KNOWLEDGABLE | 12723 |
| EMPATHY | V18. INDIVIDUAL ATTENTION | EMPLOYEES#INDIVIDUAL ATTENTION | 75 |
| EMPATHY | V20. EMPLOYEES WHO GIVE CUSTOMERS PERSONAL ATTENTION, HOLSERV(+) | EMPLOYEES#CARING | 916 |
| EMPATHY | V21. CUSTOMERS_INTEREST_AT_HEART | EMPLOYEES#CUSTOMER_CENTERED | 37073 |
| EMPATHY | V22. UNDERSTAND_CUSTOMERS_SPECIAL_NEEDS AND HOLSERV(+) | EMPLOYEES#UNDERSTANDING_SPEC IAL_NEEDS | 23306 |
| EMPATHY | V19 CONVENIENT OPERATING HOURS | RELIABILITY#CONVENIENT_OPERATI NG_HOURS | 8293 |
| RELIABILITY | V5. HOTEL FULFILLS ITS PROMISES AT THE TIME THE TIME THEY HAVE SPECIFIED REL.LODG. | RELIABILITY#SERVICE_ON_TIME_WH EN PROMISED | 3265 |
| RELIABILITY | V7. THE HOTEL PERFORMS THE SERVICE RIGHT AT THE FIRST TIME (EFFICIENCY, RELIABILITY) | RELIABILITY#EFFICIENCY | 2632 |
| RELIABILITY | V6. PROBLEM_ADMINISTRATION and HOLSERV(+) | RELIABILITY#PROBLEM_ADMINISTR ATION | 7546 |
| RELIABILITY | V8 KEEPS_PROMISES_ON_TIME LODG.REL. DEPENDABLE/CONSISTENT | RELIABILITY#DEPENDABLE | 24865 |
| ASSURANCE | V9.ERROR_FREE_CODE | RELIABILITY#ERROR_FREE_CODE | 7120 |
| ASSURANCE | V14. EMPLOYEES_INSTILLING_CONFIDENCE | RELIABILITY#INSTILLING_CONFIDEN CE | 15144 |
| ASSURANCE | V15 SAFETY AND SECURITY | RELIABILITY#SECURITY | 5070 |
| | | **TOTAL** | 286,158 |

Moreover, Table 11. shows the frequencies summed up to the basic SERVQUAL categorisations. The total number of SERVQUAL dimensions related to the total number of sentences is 286,158 or 46.62% of the reviewed sentences. This number means that the SERVQUAL dimensions are an essential part of online reviews, but there are also categories discussed that might go annoticed. Additionally, the TANBIBLES category is the most prominent dimension with 90,606 related sentences, and RESPONSIVENESS is the one with the lowest frequency with 13,968 counts or 2.28% of the total class predictions. As a result, the latter dimensions are the most under-represented in relation to the total amount of dimensions commented by the reviewers.

| Table 11 SERVQUAL | | | |
|---|---|---|---|
| | **Count** | **Percentage** | **Percentage of Total** |
| TANGIBLES | 90606 | 31.66% | 14.76% |
| RELIABILITY | 45428 | 15.88% | 7.40% |
| RESPONSIVENESS | 13968 | 4.88% | 2.28% |
| ASSURANCE | 66493 | 23.24% | 10.83% |
| EMPATHY | 69663 | 24.34% | 11.35% |
| **TOTAL** | 286158 | 100.00% | 46.62% |

Table 11 presents the SERVQUAL categorisation, as suggested by Boon et al. (2014). There is an overlap in these categorisations with the HOLSERV results since the HOLSERV+ model has been developed in an effort to match the HOLSERV scale dimensions with topics discussed in online reviews. HOLSERV+ dimensions explain 62,22% of the suggested model. This is to be expected since the HOLSERV+ model has been designed to be used precisely with online reviews. The most prominent dimension in Table 12 is SURROUNDINGS, with 175,381 appearances of this dimension in the corpus, representing 28,57% of the 613,790 sentences. The dimension least discussed in reviews according to HOLSERV(+) dimensions is RELIABILITY, with 11,390 instances.

| Table 12 **HOLESRV/HOLSERV+** | | |
|---|---|---|
| TANGIBLES | ROOM | 67,535 |
| TANGIBLES | FACILITIES | 84,716 |
| TANGIBLES | SURROUNDINGS | 175,381 |
| RELIABILITY | RELIABILITY | 11,390 |
| EMPLOYEES | EMPLOYEES | 42,892 |
| | **TOTAL** | 339,022 |

At this stage, the present research attempts to break down these dimensions into more categories based on Boon's et al. (2014) related keywords. TABLE 13 presents all the dimensions analyzed in this part of the research for both SERVQUAL and HOLSERV(+) with the researched extended categorisations of the HOLSERV+ model. The suggested presentation gives analysts and researchers the possibility to have a more in-depth and multi-point-of-view understanding of the dimensions discussed by the reviewers. In the first column appear the dimensions according to SERVQUAL. The second column shows the relation with the HOLSERV(+) dimensions. The third column presents the categories annotated by the deep neural network algorithm. The fifth column shows how many times the category has been discussed in the annotated sentences, and finally, the sixth column presents the percentage of the category's appearances to the 613,790 sentences.

Most of the Tangibles dimensions are at the top preferences of reviewers. The dimensions less discussed are EMPATHY, RESPONSIVENESS, and RELIABILITY. The category with the highest number of instances is FACILITIES#MISCELLANEOUS, that is 13.80% of the corpus. This is an indication that the specific category could be divided into more detailed categorisation. Additionally, the intangible dimensions seem to be discussed a lot less than tangible categories. Among the lowest categories discussed are the RESPONSIVENESS categories, which are related to the eagerness, efficiency, and staff's appearance. Similarly, the EMPATHY categories of Caring and Individual Attention are the ones with the least number of references from reviewers.

**TABLE 13 HOLSERV (+) CATEGORIZATION**

| DIMENSIONS' RELATION | | | | |
|---|---|---|---|---|
| **SERVQUAL Dimensions** | **HOLSERV(+) RELATION** | **Categories** | **Count** | **Percentages** |
| TANGIBLES | HOLSERV | ROOM#DESIGN_FEATURES | 31,790 | 5.179% |
| TANGIBLES | HOLSERV+ | ROOM#CLEANLINESS | 14,584 | 2.376% |
| TANGIBLES | HOLSERV+ | ROOM#COMFORT | 25,095 | 4.089% |
| TANGIBLES | HOLSERV+ | ROOM#EQUIPM ENT | 27,856 | 4.538% |
| TANGIBLES | HOLSERV | FACILITIES#DESIGN_FEATURES | 54,150 | 8.822% |
| TANGIBLES | HOLERV+ | FACILITIES#MISCELLANEOUS | 84,716 | 13.802% |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#LOCATION | 62,829 | 10.236% |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#NEARBY_AMENITIES | 66,202 | 10.786% |

| | | | | |
|---|---|---|---|---|
| TANGIBLES | HOLSERV+ | SURROUNDINGS#TRANSPORT | 11,718 | 1.909% |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#ATTRACTIONS | 34,632 | 5.642% |
| TANGIBLES | HOLSERV, HOLSERV+ (EMPLOYEES) | SERVICE#CLEANLINESS | 2,689 | 0.438% |
| RESPONSIVENESS | HOLSERV, HOLSERV+ (EMPLOYEES) | EMPLOYEES#APPEARANCE | 1,977 | 0.322% |
| RESPONSIVENESS | HOLSERV | EMPLOYEES#SCHEDULE_ACCURACY | 1,118 | 0.182% |
| RESPONSIVENESS | HOLSERV, HOLSERV+ (EMPLOYEES) | EMPLOYEES#PROMPTNESS | 7,359 | 1.199% |
| RESPONSIVENESS | HOLSERV, HOLSERV+ (RELIABILITY) | EMPLOYEES#EAGERNESS | 3,844 | 0.626% |
| RESPONSIVENESS | HOLSERV | EMPLOYEES#AT_CUSTOMERS_DISPOSAL | 1,647 | 0.268% |
| ASSURANCE | HOLSERV, HOLSERV+ | EMPLOYEES#COURTEOUS | 33,556 | 5.467% |
| ASSURANCE | HOLSERV | EMPLOYEES#KNOWLEDGABLE | 12,723 | 2.073% |
| EMPATHY | HOLSERV | EMPLOYEES#INDIVIDUAL ATTENTION | 75 | 0.012% |
| EMPATHY | HOLSERV | EMPLOYEES#CARING | 916 | 0.149% |
| EMPATHY | HOLSERV | EMPLOYEES#CUSTOMER_CENTERED | 37,073 | 6.040% |
| EMPATHY | HOLSERV | EMPLOYEES#UNDERSTANDING_SPECIAL_NEEDS | 23,306 | 3.797% |
| RELIABILITY | HOLSERV | RELIABILITY#SERVICE_ON_TIME_WHEN PROMISED | 3,265 | 0.532% |
| RELIABILITY | HOLSERV | RELIABILITY#EFFICIENCY | 2,632 | 0.429% |
| RELIABILITY | HOLSERV, HOLSERV+ | RELIABILITY#PROBLEM_ADMINISTRATION | 7,546 | 1.229% |
| RELIABILITY | HOLSERV | RELIABILITY#DEPENDABLE | 24,865 | 4.051% |
| ASSURANCE | HOLSERV | RELIABILITY#ERROR_FREE_CODE | 7,120 | 1.160% |
| ASSURANCE | HOLSERV | RELIABILITY#INSTILLING_CONFIDENCE | 15,144 | 2.467% |
| ASSURANCE | HOLSERV | RELIABILITY#SECURITY | 5,070 | 0.826% |
| EMPATHY | HOLSERV | RELIABILITY#CONVENIENT_OPERATING_HOURS | 8,293 | 1.351% |
| | | **TOTAL** | 613,790 | 100.000% |

### 4.3.2 Descriptive Analysis and Development of the Proposed Model

For the descriptive analysis, as described by (Boon, Bonera and Bigi, 2013), an extensive word frequency list is generated by the dataset retrieved from TripAdvisor.com for Crete's hotels. The top 1000 words of this database are chosen for further editing. We remove stopwords. Also, words that cannot be assigned are either labelled ambiguous (isolated for further discussion) or unclassified (ignored). Table 14 presents the top 150 words, and the table with the top 1000 words can be found in Appendix B.

| TABLE 14. FREQUENCY TABLE - TOP 150 WORDS | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| N | Frequency | TopNouns | N | Frequency | TopNouns | N | Frequency | TopNouns | N | Frequency | TopNouns | N | Frequency | TopNouns |
| 1 | 104100 | hotel | 31 | 7630 | center | 61 | 4531 | coffee | 91 | 3085 | end | 121 | 2122 | anything |
| 2 | 46893 | room | 32 | 7556 | holiday | 62 | 4460 | sun | 92 | 3046 | table | 122 | 2118 | sand |
| 3 | 40778 | beach | 33 | 7311 | price | 63 | 4429 | rest | 93 | 3030 | fruit | 123 | 2107 | one |
| 4 | 30846 | staff | 34 | 7268 | crete | 64 | 4244 | front | 94 | 3028 | thing | 124 | 2085 | hospitality |
| 5 | 30635 | pool | 35 | 7110 | dinner | 65 | 4094 | way | 95 | 3004 | team | 125 | 2077 | manager |
| 6 | 26764 | sea | 36 | 7061 | village | 66 | 4068 | year | 96 | 2984 | heraklion | 126 | 2075 | toilet |
| 7 | 22469 | breakfast | 37 | 6881 | terrace | 67 | 4029 | chania | 97 | 2949 | airport | 127 | 2062 | cuisine |
| 8 | 21614 | food | 38 | 6875 | lot | 68 | 3938 | money | 98 | 2899 | point | 128 | 2036 | right |
| 9 | 20862 | day | 39 | 6487 | city | 69 | 3885 | garden | 99 | 2837 | wifi | 129 | 2016 | kindness |
| 10 | 17591 | everything | 40 | 6463 | morning | 70 | 3793 | home | 100 | 2752 | wine | 130 | 1971 | board |
| 11 | 15670 | view | 41 | 6357 | floor | 71 | 3660 | animation | 101 | 2640 | house | 131 | 1967 | atmosphere |
| 12 | 13701 | location | 42 | 6325 | quality | 72 | 3655 | problem | 102 | 2554 | value | 132 | 1966 | furniture |
| 13 | 13647 | place | 43 | 6038 | nothing | 73 | 3555 | swimming | 103 | 2497 | building | 133 | 1947 | entrance |
| 14 | 13475 | time | 44 | 6021 | bus | 74 | 3513 | structure | 104 | 2490 | couple | 134 | 1944 | attention |
| 15 | 13224 | service | 45 | 5849 | buffet | 75 | 3492 | vacation | 105 | 2479 | access | 135 | 1924 | change |
| 16 | 12687 | restaurant | 46 | 5623 | shower | 76 | 3415 | lunch | 106 | 2445 | addition | 136 | 1922 | season |
| 17 | 11778 | area | 47 | 5459 | kitchen | 77 | 3309 | part | 107 | 2438 | bay | 137 | 1914 | taste |
| 18 | 11379 | water | 48 | 5440 | cleaning | 78 | 3290 | cleanliness | 108 | 2408 | juice | 138 | 1900 | peace |
| 19 | 11123 | bar | 49 | 5390 | something | 79 | 3212 | side | 109 | 2407 | entertainment | 139 | 1889 | resort |
| 20 | 10589 | car | 50 | 5373 | owner | 80 | 3209 | welcome | 110 | 2369 | accommodation | 140 | 1884 | meat |
| 21 | 10212 | bathroom | 51 | 5372 | bed | 81 | 3188 | parking | 111 | 2366 | number | 141 | 1874 | clean |
| 22 | 9752 | stay | 52 | 5263 | street | 82 | 3178 | walk | 112 | 2318 | foot | 142 | 1862 | stop |
| 23 | 9596 | family | 53 | 5253 | bit | 83 | 3166 | course | 113 | 2318 | person | 143 | 1860 | club |
| 24 | 9542 | night | 54 | 5184 | road | 84 | 3161 | arrival | 114 | 2304 | music | 144 | 1850 | complex |
| 25 | 9037 | week | 55 | 5147 | town | 85 | 3158 | fridge | 115 | 2282 | level | 145 | 1849 | tour |
| 26 | 8948 | reception | 56 | 5109 | island | 86 | 3140 | tv | 116 | 2244 | care | 146 | 1834 | hour |
| 27 | 8734 | air | 57 | 4802 | conditioning | 87 | 3132 | distance | 117 | 2207 | space | 147 | 1809 | kitchenette |
| 28 | 8214 | evening | 58 | 4779 | kind | 88 | 3121 | door | 118 | 2177 | fact | 148 | 1807 | selection |
| 29 | 8039 | balcony | 59 | 4726 | everyone | 89 | 3101 | noise | 119 | 2173 | supermarket | 149 | 1794 | greece |
| 30 | 7695 | apartment | 60 | 4650 | choice | 90 | 3090 | trip | 120 | 2158 | star | 150 | 1753 | bedroom |

One of the main customer interests expressed through online reviews when it comes to their accommodation is the relation of hotel/room/services to the value and price of each aspect. Although value has not been an aspect of service quality assessment tools in the past, this is an indication that should be included in the categorisation and maybe that it should be included in future offline questionnaires. Moreover, although Parasuraman, Zeithaml and Berry (1988) did not include value as an aspect of the dimensions in their models (Parasuraman, Zeithaml and Berry, 1994, 1985, 1988), they included the quality assessment tool they created for websites (E-S-QUAL) (Parasuraman, Zeithaml and Malhotra, 2005; Parasuraman, Zeithaml and Berry, 1985, 1994, 1988). These might point out that the interest of accommodation providers and receivers has expanded, including these aspects and internet-related information.

Based on the descriptive analysis, in addition to price and value related attributes, we also include the aspects of comfort quality and quality in relation to bathroom, hotel, facilities, and room amenities. Additionally we include, internet, bathroom, hotel, facilities, in relation to tangibles, and management in relation to the reliability of the company. Finally, based on the initial analysis, we perceive employee caring, courteous, and understanding customers' special needs as sub-categorisations of customer_centered services. The annotation of the new enhanced categorisation is based on the initial process we followed for the SERVQUAL and HOLSERV(+) categorisation.

For the annotation, we start from the SEMEVAL golden annotation system for hotels (Pontiki, M., Galanis, D., Papageorgiou, H., Manandhar, S., and Androutsopoulos, I., 2016) and customize it to fit the newly developed categorisation, which is based on the SERVQUAL and HOLSERV(+) classification. The annotated data will be the training data fed to the aspect CNN classification algorithm later. The two linguist experts (with linguistic studies and multi-year interpretation experience) have been asked to assess the categorisation and assign three words to each category, which will aid during the annotation process. A hospitality and tourism expert has evaluated the final table once more and suggested the final correction in the model.

Two annotators carry out three trials to validate the annotation schema. For all the trials, we start from the newly assembled annotation system for accommodation. Each annotator classifies an aspect for each review, which is the noun related to the annotation, using an Excel file with filters created for this specific purpose. Consequently, the annotator assigns an aspect category and its sentiment for each review. This means that in a long sentence, there might be different aspects related to one or more aspect categories. The annotators have been asked to keep track of the problems they face during the annotation process(Almagrabi, Malibari and Mcnaught, 2018). Before proceeding to the final annotation process of annotating the SERVQUAL and HOLSERV(+) schema, and the final schema (with the new categorisations), we consulted the three experts.

The resulting categorisation, along with the problems that the annotators faced in both training files SERVQUAL and HOLSERV(+) and the enhanced aspect categorisation, have been discussed with the linguist experts. The suggestions were then discussed with the tourism and hospitality expert, and based on his comments and suggestions, the final table was created.

During the annotation process, we found that EMPLOYEES#CARING, UNDERSTANDING, INDIVIDUAL_ATTENTION, AT_CUSTOMERS_DISPOSAL can be grouped under the CUSTOMER_CENTERED category. This observation means that the more detailed information will be used from the annotators, except if the information can be grouped there. In this case, they define the entity as CUSTOMER_CENTERED. Whenever we need statistics in CUSTOMER_CENTERED, we will use its sub-grouping categories as well.

Nest, the final categories that were used for annotation and for the aspect analysis are presented. Specifically, the linguist experts:

- changed the classification ROOM#EQUIPMENT to ROOM#FURNITURE because there was an overlap of meaning between ROOM#EQUIPMENT and ROOM_AMENITIES#EQUIPMENT. The hospitality and tourism expert also approved this change.
- Changed HOTEL#MISC to HOTEL#CUSTOMIZED_TO_SPECIFIC_CUSTOMER_NEEDS. We noticed that the Annotated sentences characterized as HOTEL#MISC refer to specific hotel types (i.e., Business Hotel, Hotel for Children, and Families). The hospitality expert finally suggested HOTEL#GUEST_CUSTOMIZED category. He suggested avoiding the definition ‘specialization’ since it has been used in other contexts (i.e., specialized forms of service - trains, planes, outdoor catering and more)
- noticed that although the categories V2. FACILITIES_VISUALLY_APPEALING, V3. EMPLOYEES NEAT-APPEARING AND HOLSERV+, are related to Employees / Services, they refer, however, to tangible situations. Therefore, we grouped the two categories under "SERVICE" and characterized them as tangibles. The tourism expert approved this change and the ones that follow as well.
- renamed the "EMPLOYEES" group to "CUSTOMER_CARE / EMPLOYEES". This change will aid in more detailed and precise analyses.

- merged V12. WILLING_TO_HELP, and V13. NEVER BUSY TO RESPOND in one category named "EAGERNESS", because there was overlapping information and meaning in these two categories.
- merged V18. INDIVIDUAL ATTENTION, V20. EMPLOYEES WHO GIVE CUSTOMERS PERSONAL ATTENTION, HOLSERV+, and V21 Customer's best interest at heart into one category named "CUSTOMER_CENTERED", because there was overlapping information and meaning in these three categories.
- renamed ERROR_FREE_CODES into WITHOUT_MISTAKES, as the latter name is more easily comprehensible.

Table 14 presents an overview of the final suggested categorisation, dimensions, and the relation between the quality assessment tools and the new categories. Group 4 suggested the most detailed version of the table where the other 3 Groups that aggregate the different levels of the Multi-Dimensional model will be presented later in the study.

| Table 14 ENHANCED CATEGORIZATION (Group 4 - detailed) | | ASPECT |
|---|---|---|
| **DIMENSION RELATION** | | **ROOM** |
| TANGIBLES | V1. MODERN_LOOKING_EQUIPMENT and HOLERV+ | ROOM#DESIGN_FEATURES |
| TANGIBLES | HOLSERV+ | ROOM#CLEANLINESS |
| TANGIBLES | HOLSERV+ | ROOM#COMFORT |
| TANGIBLES | HOLSERV+ | ROOM_AMENITIES#USER_FRIENDLY |
| TANGIBLES | HOLSERV+ | ROOM_AMENITIES#EQUIPMENT |
| VALUE | DESCRIPTIVE ANALYSIS | ROOM_AMENITIES#PRICES |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM_AMENITIES#QUALITY |
| VALUE | DESCRIPTIVE ANALYSIS | ROOMI#OVERALL_VALUE |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#INTERNET |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#BED_COMFORT |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#SIZE |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#FURNITURE |
| TANGIBLES | DESCRIPTIVE ANALYSIS | BATHROOM#CLEANLINESS |
| TANGIBLES | DESCRIPTIVE ANALYSIS | BATHROOM#EQUIPMENT |
| TANGIBLES | DESCRIPTIVE ANALYSIS | BATHROOM#SIZE |
| **DIMENSION RELATION** | | **HOTEL** |
| TANGIBLES | V2. MODERN-LOOKING_FACILITIES | HOTEL#DESIGN_FEATURES |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#MISCELLANEOUS |
| VALUE | DESCRIPTIVE ANALYSIS | HOTEL#PRICES |

| | | |
|---|---|---|
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#QUALITY |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#COMFORT |
| VALUE | DESCRIPTIVE ANALYSIS | HOTELl#OVERALL_VALUE |
| **DIMENSION RELATION** | | **FACILITIES** |
| TANGIBLES | V2. FACILITIES_VISUALLY_APPEALING | FACILITIES#DESIGN_FEATURES |
| TANGIBLES | HOLERV+ | FACILITIES#MISCELLANEOUS |
| VALUE | DESCRIPTIVE ANALYSIS | FACILITIES#PRICES |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FACILITIES#QUALITY |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FACILITIES#COMFORT |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FACILITIES#CLEANLINESS |
| **DIMENSION RELATION** | | **FOOD_DRINKS** |
| TANGIBLES | HOLSERV+ | FOOD_DRINKS#STYLE_OPTIONS |
| TANGIBLES | HOLSERV+ | FOOD_DRINKS#QUALITY |
| VALUE | DESCRIPTIVE ANALYSIS | FOOD_DRINKS#PRICES |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FOOD_DRINKS#OVERALL_VALUE |
| **DIMENSION RELATION** | | **SURROUNDINGS** |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#LOCATION |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#NEARBY_AMENITIES |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#TRANSPORT |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#ATTRACTIONS |
| **DIMENSION RELATION** | | **EMPLOYEES** |
| RESPONSIVENESS | V3. EMPLOYEES NEAT-APPEARING AND HOLSERV+ | SERVICE#APPEARANCE |
| TANGIBLES | V4. EMPLOYEES_NEAT-APPEARING AND CLEAN_MATERIALS AND HOLSERV+ | SERVICE#CLEANLINESS |
| RESPONSIVENESS | V10. INFORMATION_ACCURACY | RESPONSIVENESS#SCHEDULE_ACCURACY |
| RESPONSIVENESS | V11. PROMPT_SERVICE / LODG.RESP. AND HOLSERV+ | RESPONSIVENESS#PROMPTNESS |
| RESPONSIVENESS | V12. WILLING_TO_HELP | RESPONSIVENESS#EAGERNESS |
| RESPONSIVENESS | V13. NEVER BUSY TO RESPOND | RESPONSIVENESS#AT_CUSTOMERS_DISPOSAL |
| ASSURANCE | V16 CONSISTENTLY COURTEOUS EMPLOYEES TOWARDS CUSTOMERS HOLSERV+ (POLITENESS) | EMPLOYEES#COURTEOUS |
| ASSURANCE | V17. KNOWLEDGE TO ANSWER CUSTOMER QUESTIONS/ LODG.ASSUR. | EMPLOYEES#KNOWLEDGABLE |
| EMPATHY | V18. INDIVIDUAL ATTENTION | EMPLOYEES#INDIVIDUAL ATTENTION |
| EMPATHY | V20. PERSONAL ATTENTION AND HOLSERV+ | EMPLOYEES#CARING |
| EMPATHY | V21. CUSTOMERS_INTEREST_AT_HEART | EMPLOYEES#CUSTOMER_CENTERED |
| EMPATHY | V22. UNDERSTAND_CUSTOMERS_SPECIAL_NEEDS AND HOLSERV+ | EMPLOYEES#UNDERSTANDING_SPECIAL_NEEDS |
| VALUE | DESCRIPTIVE ANALYSIS | SERVICE#PRICE |
| **DIMENSION RELATION** | | **RELIABILITY** |
| RELIABILITY | V5. HOTEL FULFILLS ITS PROMISES AT THE TIME THE TIME THEY HAVE SPECIFIED | RELIABILITY#SERVICE_ON_TIME_WHEN PROMISED |

| | | |
|---|---|---|
| RELIABILITY | V7. THE HOTEL PERFORMS THE SERVICE RIGHT AT THE FIRST TIME (EFFICIENCY, RELIABILITY) | RELIABILITY#EFFICIENCY |
| RELIABILITY | V6. PROBLEM_ADMINISTRATION and HOLSERV+ | RELIABILITY#PROBLEM_ADMINISTRATION |
| RELIABILITY | V8 KEEPS_PROMISES_ON_TIME LODG.REL. DEPENDABLE/CONSISTENT | RELIABILITY#DEPENDABLE |
| ASSURANCE | V9.ERROR_FREE_CODE | RELIABILITY#ERROR_FREE_CODE |
| ASSURANCE | V14. EMPLOYEES_INSTILLING_CONFIDENCE | RELIABILITY#INSTILLING_CONFIDENCE |
| ASSURANCE | V15 SAFETY AND SECURITY | RELIABILITY#SECURITY |
| EMPATHY | V19 CONVENIENT OPERATING HOURS | RELIABILITY#CONVENIENT_OPERATING_HOURS |
| RELIABILITY | DESCRIPTIVE ANALYSIS | RELIABILITY#MANAGEMENT |

### 4.3.3 Multi-Dimensional Model Analysis

### Convolutional Neural Network Customization

The deep learning convolutional neural network script is customized for the specific needs of the enhanced classification model. In this case, the sequential model with a linear stack of layers is also run on a Windows ec2 instance of a German Server of Amazon Web Services. Since the information to be processed needs a significant amount of temporal memory, an x1e.2xlarge ec2 server with 244Gb SSD memory is used.

The Convolutional Neural Feed Forward Network model consists of a dense layer with 512 nodes and an input shape of a 6000-word embedding layer activated by relu nonlinear activation function. The layers include Dense, Activation and Dropout layers.  The nonlinear function makes it possible to transform the information so that the resulting processed data can be classified into different classes.

After that, a dropout layer is activated to prevent overfitting and reduce the size, along with a dense layer with nodes and a ReLu activation function. Finally, the output layer comprised 57 neurons, one for each category, through a dense layer activated with sigmoid function. This makes it possible to achieve probability distribution among the 57 classes that we want to predict in the enhanced model. Softmax, sigmoid activations were both tested, but sigmoid returned the best results. The training and extraction of the multi-class model are based on the binary cross-entropy classifier. The model is trained with the pre-labelled dataset specifically for the 57 enhanced category model.

The Bag of Words word embedding technique is used to encode the review sentences in vectors. Additionally, the aspect categories are encoded to a binary variable (dummy variable) before fitted to the test dataset. Eleven epochs at a batch size of 64 samples is the chosen fitting process for the model, to avoid overfitting while reaching optimal results. Additionally, the model is run with Adam optimizer. The Learning rate, as the term's name implies, specifies the learning rate of the deep neural model during the training process. For this model, the trials showed that it achieves optimal results at a constant learning rate of 0.01.

## Cross-Validation and Model Evaluation

For the Cross-validation, the training data are split into two datasets. 90% of the initial training data are fed to the model in order to train it, and the remaining 10% per cent acts as the test data. The test data's predicted values are cross-validated to the initial training data's actual values. The result gives an estimation of the validity of the model. The aforementioned compiled model performed well, returning 70% F-metric accuracy.

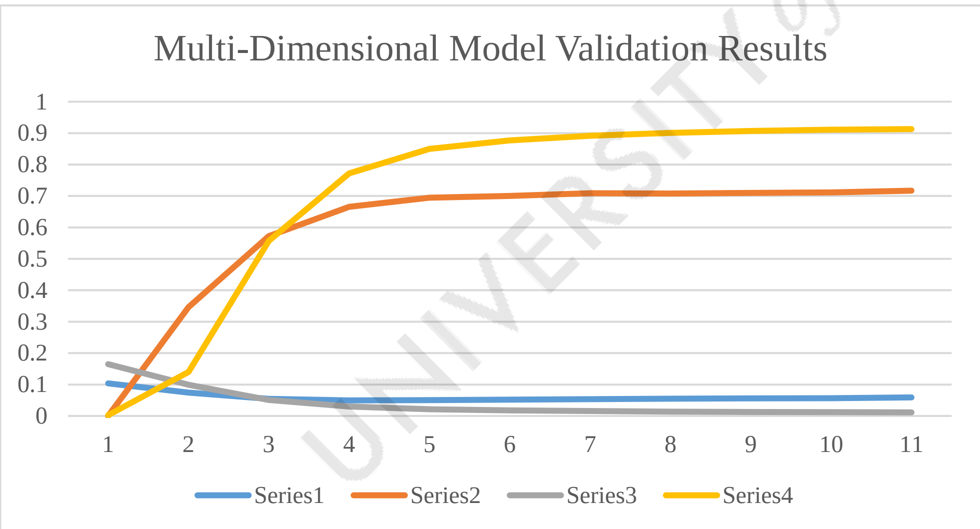



**FIGURE 13 MULTI-DIMENSIONAL MODEL VALIDATION RESULTS**

Model evaluation

The evaluation of the model follows the evaluation method of SemEval 2014 using F-Measure (Pontiki and Pavlopoulos, 2014). Additionally, Precision, Recall, and Logarithmic Loss are used for the evaluation of the CNN model. The results are presented in the follwing Table and Figure.

Table 15 Accuracy Metrics

| | logloss | F1 | Precision | Recall |
|---|---|---|---|---|
| 0 | 0.181097247 | 0.00176491 | 0.001202569 | 0.012720848 |
| 1 | 0.084327381 | 0.005483015 | 0.10553592 | 0.002826855 |
| 2 | 0.055801889 | 0.258980959 | 0.832314954 | 0.161130742 |
| 3 | 0.032304356 | 0.596591195 | 0.839390872 | 0.469611308 |
| 4 | 0.020380905 | 0.77383258 | 0.882854664 | 0.692226148 |
| 5 | 0.014823266 | 0.843835736 | 0.898884894 | 0.796819788 |
| 6 | 0.011784529 | 0.878315953 | 0.91318913 | 0.846996466 |
| 7 | 0.010225367 | 0.893406513 | 0.920975594 | 0.86819788 |
| 8 | 0.009466602 | 0.901354823 | 0.920252086 | 0.88409894 |
| 9 | 0.008621882 | 0.913627522 | 0.929182297 | 0.899293286 |
| 10 | 0.007824847 | 0.913824061 | 0.928067981 | 0.900706714 |

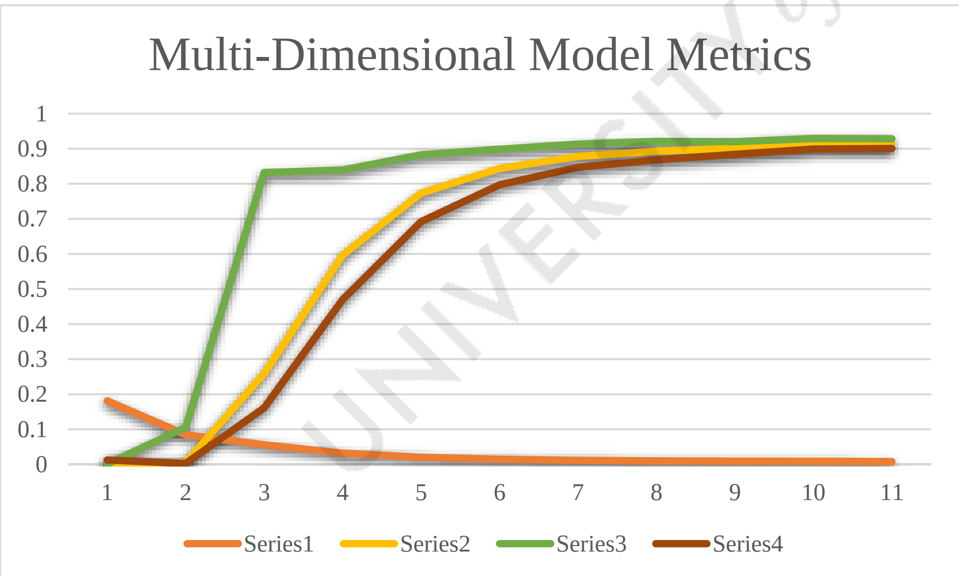



FIGURE 14 MULTI-DIMENSIONAL MODEL METRICS

## ANALYSIS OF ENHANCED CATEGORISATION

Results

The analysis of the categorisations given from the proposed model's resulted, as presented in the following figure, to 30% of the discussed topics to come from the SERVQUAL scale, 36% from the HOLSERV+ categorisation and 34% of the online reviews discussed topics to come from the Descriptive Analysis emerging categorisation of this thesis.

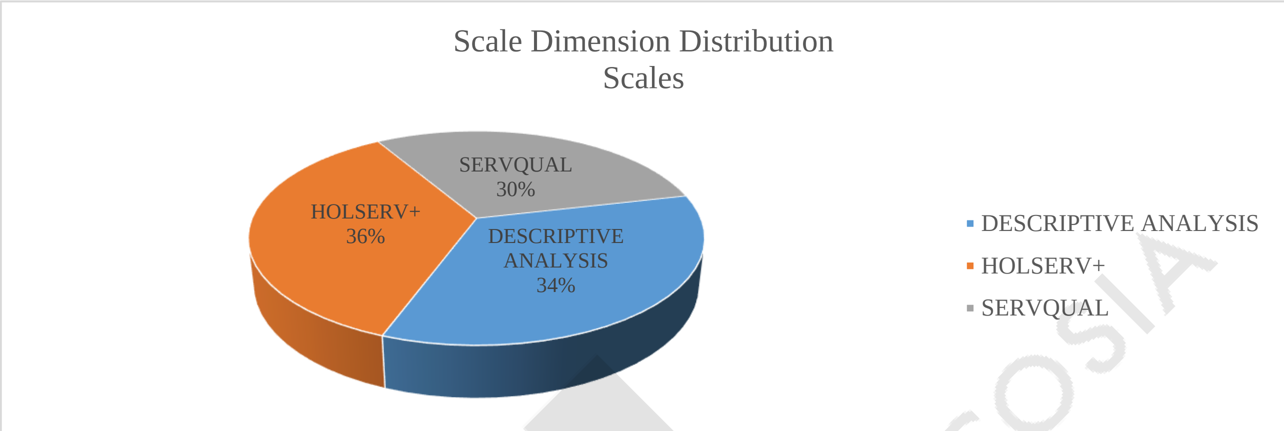



**FIGURE 15 SCALE DIMENSION DISTRIBUTION**

The results from the Enhanced Categorization Model are presented in Table 16. The frequencies and percentages are presented in a colour-heatmap where the highest value is dark blue, and the lowest is dark red. In Table 17. the same dimensions are presented sorted by value, from highest to lowest.

| Table 16 ENHANCED CATEGORIZATION (Group 4 - detailed) | | ASPECT | | |
|---|---|---|---|---|
| **DIMENSIONS** | **RELATION** | **ROOM** | **Count** | **Percentage** |
| TANGIBLES | SERVQUAL, HOLSERV | ROOM#DESIGN_FEATURES | 25,236 | 3.688% |
| TANGIBLES | HOLSERV+ | ROOM#CLEANLINESS | 7,621 | 1.114% |
| TANGIBLES | HOLSERV+ | ROOM#COMFORT | 15,094 | 2.206% |
| TANGIBLES | HOLSERV+ | ROOM_AMENITIES#USER_FRIENDLY | 2,127 | 0.311% |
| TANGIBLES | HOLSERV+ | ROOM_AMENITIES#EQUIPMENT | 6,045 | 0.883% |

| | | | | |
|---|---|---|---|---|
| VALUE | DESCRIPTIVE ANALYSIS | ROOM_AMENITIES#PRICES | 1,258 | 0.184% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM_AMENITIES#QUALITY | 2,715 | 0.397% |
| VALUE | DESCRIPTIVE ANALYSIS | ROOM#OVERALL_VALUE | 19,403 | 2.836% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#PRICES | 2,841 | 0.415% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#INTERNET | 2,032 | 0.297% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM_AMENITIES#BED_COMFORT | 3,353 | 0.490% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#SIZE | 2,501 | 0.365% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#FURNITURE | 3,881 | 0.567% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | BATHROOM#CLEANLINESS | 6,462 | 0.944% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | BATHROOM#EQUIPMENT | 4,760 | 0.696% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | BATHROOM#SIZE | 274 | 0.040% |
| **DIMENSIONS** | **RELATION** | **HOTEL** | | |
| TANGIBLES | SERVQUAL, HOLSERV | HOTEL#DESIGN_FEATURES | 7,166 | 1.047% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#GUEST_CUSTOMIZED | 630 | 0.092% |
| VALUE | DESCRIPTIVE ANALYSIS | HOTEL#PRICES | 13,355 | 1.952% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#QUALITY | 4,688 | 0.685% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#COMFORT | 13,860 | 2.025% |
| VALUE | DESCRIPTIVE ANALYSIS | HOTEL#OVERALL_VALUE | 8,019 | 1.172% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#CLEANLINESS | 16,488 | 2.410% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#AMBIANCE | 5,328 | 0.779% |
| | | | | |
| **DIMENSIONS** | **RELATION** | **FACILITIES** | | |
| TANGIBLES | SERVQUAL, HOLSERV | FACILITIES#DESIGN_FEATURES | 13,080 | 1.911% |
| TANGIBLES | HOLERV+ | FACILITIES#MISCELLANEOUS | 23,997 | 3.507% |
| VALUE | DESCRIPTIVE ANALYSIS | FACILITIES#PRICES | 5,677 | 0.830% |

| | | | | |
|---|---|---|---|---|
| TANGIBLES | DESCRIPTIVE ANALYSIS | FACILITIES#QUALITY | 11,705 | 1.711% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FACILITIES#COMFORT | 13,604 | 1.988% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FACILITIES#CLEANLINESS | 4,597 | 0.672% |
| **DIMENSIONS** | **RELATION** | **FOOD_DRINKS** | | |
| TANGIBLES | HOLSERV+ | FOOD_DRINKS#STYLE_OPTIONS | 22,200 | 3.244% |
| TANGIBLES | HOLSERV+ | FOOD_DRINKS#QUALITY | 15,351 | 2.243% |
| VALUE | DESCRIPTIVE ANALYSIS | FOOD_DRINKS#PRICES | 9,036 | 1.321% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FOOD_DRINKS#OVERALL_VALUE | 11,468 | 1.676% |
| **DIMENSIONS** | **RELATION** | **SURROUNDINGS** | | |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#LOCATION | 69,817 | 10.203% |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#NEARBY_AMENITIES | 58,448 | 8.541% |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#TRANSPORT | 8,667 | 1.267% |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#ATTRACTIONS | 38,954 | 5.693% |
| **DIMENSIONS** | **RELATION** | **SERVICE / EMPLOYEES** | | |
| TANGIBLES | SERVQUAL, HOLSERV | SERVICE#APPEARANCE | 1,859 | 0.272% |
| TANGIBLES | SERVQUAL, HOLSERV | SERVICE#CLEANLINESS | 4,975 | 0.727% |
| VALUE | DESCRIPTIVE ANALYSIS | SERVICE#PRICE | 753 | 0.110% |
| **DIMENSIONS** | **RELATION** | **CUSTOMER CARE / EMPLOYEES** | | |
| RESPONSIVENESS | SERVQUAL, HOLSERV | CUSTOMER_CARE#SCHEDULE_ACCURACY | | |
| RESPONSIVENESS | SERVQUAL, HOLSERV | CUSTOMER_CARE#PROMPTNESS | 11,227 | 1.641% |
| RESPONSIVENESS | SERVQUAL, HOLSERV | CUSTOMER_CARE#EAGERNESS | 7,140 | 1.043% |
| ASSURANCE | SERVQUAL, HOLSERV | CUSTOMER_CARE#COURTEOUS | 18,549 | 2.711% |
| ASSURANCE | SERVQUAL, HOLSERV | CUSTOMER_CARE#KNOWLEDGABLE_and_SKILLFUL | 18,897 | 2.762% |
| EMPATHY | SERVQUAL, HOLSERV | CUSTOMER_CARE#CUSTOMER_CENTERED | 32,963 | 4.817% |
| EMPATHY | SERVQUAL, HOLSERV | CUSTOMER_CARE#UNDERSTANDING_SPECIAL_NEEDS | 16,661 | 2.435% |
| **DIMENSIONS** | **RELATION** | **SOUNDNESS** | | |
| EMPATHY | SERVQUAL, HOLSERV | SOUNDNESS#CONVENIENT_OPERATING_HOURS | 10,221 | 1.494% |

| | | | | |
|---|---|---|---|---|
| RELIABILITY | SERVQUAL, HOLSERV | SOUNDNESS#SERVICE_ON_TIME_WHEN_PROMISED | 1,254 | 0.183% |
| RELIABILITY | SERVQUAL, HOLSERV | SOUNDNESS#EFFICIENCY | 670 | 0.098% |
| RELIABILITY | SERVQUAL, HOLSERV | SOUNDNESS#PROBLEM_ADMINISTRATION | 4,444 | 0.649% |
| RELIABILITY | SERVQUAL, HOLSERV | SOUNDNESS#RECOMMENDABLE | 36,477 | 5.331% |
| RELIABILITY | DESCRIPTIVE ANALYSIS | SOUNDNESS#MANAGEMENT | 1,923 | 0.281% |
| ASSURANCE | SERVQUAL, HOLSERV | SOUNDNESS#WITHOUT_MISTAKES | 3,675 | 0.537% |
| ASSURANCE | SERVQUAL, HOLSERV | SOUNDNESS#INSTILLING_CONFIDENCE | 26,865 | 3.926% |
| ASSURANCE | SERVQUAL, HOLSERV | SOUNDNESS#SECURITY | 3,993 | 0.584% |
| | | **TOTAL** | **684,284** | **100.000%** |

The 69.062 reviews were split into 684.284 sentences. The most substantial group of dimensions remains the Surroundings group. SURROUNDINGS#LOCATION counts 62.317 sentences, which are 9.10% of the total annotated sentences. ROOM#PRICES covers only 281 sentences.

As can be seen both in the table but maybe more clearly in the next figure (fig. 16), the Tangibles dimension is the most discussed, and the least discussed dimension is Responsiveness. The second most discussed dimension is Value, with 10.35% of references from Visitors. Value is one of the novel dimensions added because of the Descriptive Analysis It is apparent that Intangibles Dimension is less discussed than Tangibles. Intangibles are the dimensions provided mostly from Quality Assessment Scales. It seems that Reviewers do not touch these topics frequently.

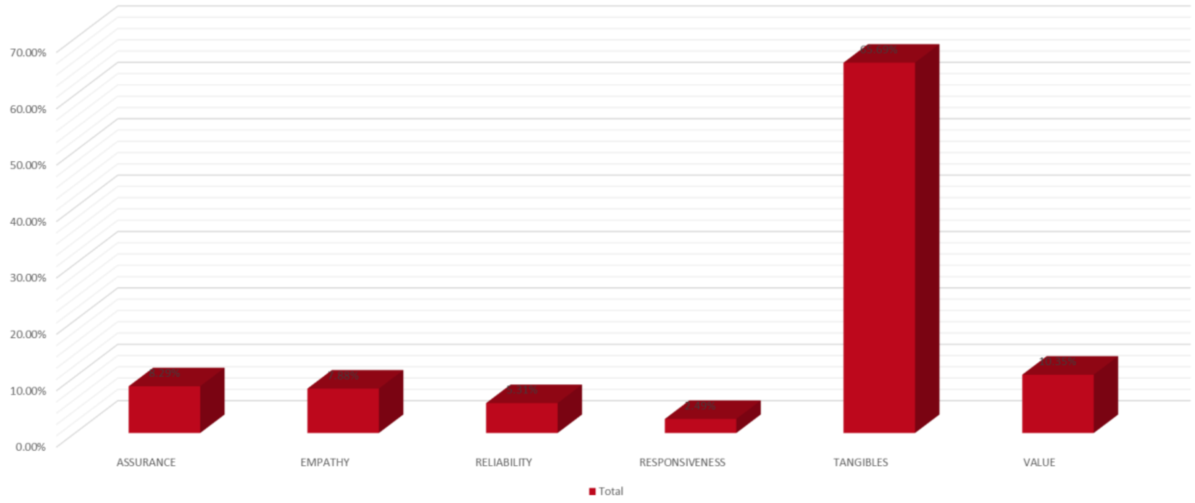



**FIGURE 16 TOP 6 DISCUSSED DIMENSIONS**

Followingly Tangibles dimensions are presented where they are grouped based on Scale (fig. 17). HOLSERV+ has provided the most discussed topics, with 47% annotated sentences from the corpus. The Descriptive Analysis emerged dimensions represent about 45% of the aspects discussed and SERVQUAL scale 8%.

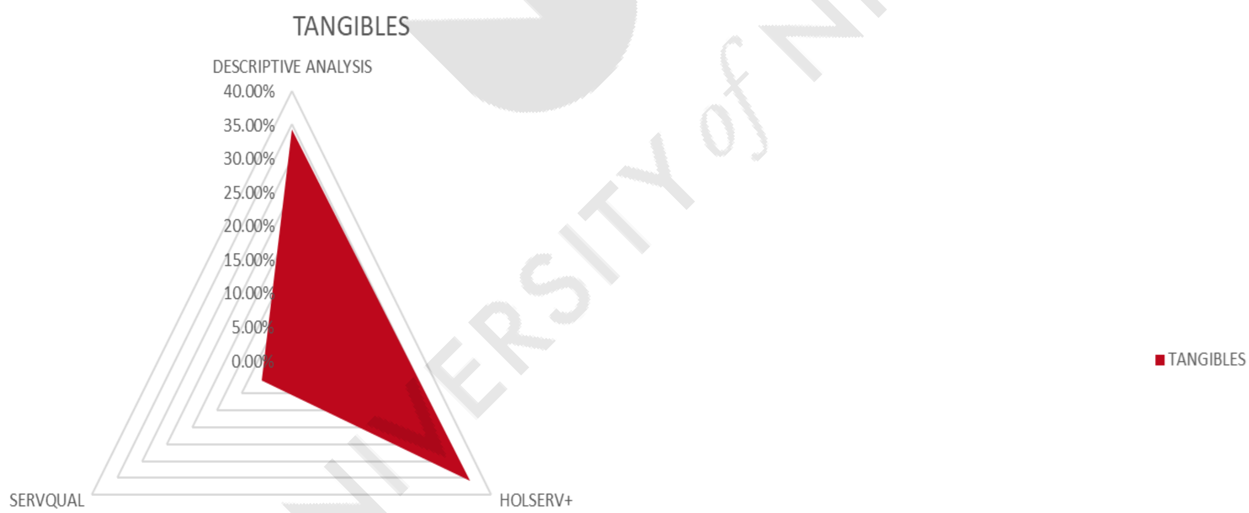



**FIGURE 17 TANGIBLES DIMESNIONS DISCUSSED IN SERVQUAL, HOLSERV+ AND DESCRIPTIVE ANALYSIS**

Getting a bit deeper (fig. 18), one could observe, as already mentioned before, that Surroundings is the most discussed dimension which belongs to the Tangibles Upper-Dimension. This is a dimension that has been added from the HOLSERV+ work and was apparent in the descriptive Analysis as well. Quality Assessment Scales have not included this dimension yet, but it seems that the location and surroundings of the Hotel are essential for the visitors.

Having a more detailed look into the mid-level dimensions, one can observe that the Surroundings, like the Location of the Hotel and nearby amenities, have been an essential part of visitors' experiences. This might be an indication that it should be taken into account from managers, and might be beneficial if added in future scales. Improving the services and surroundings quality might aid in elevating the Visitors'experiences. An example could be for an accommodation provider to add a shuttle service to the airport, if found that the visitors complained about how difficult it is to get to the airport from the hotel.

On the other hand, Intangibles Dimensions are not that often mentioned by reviewers. This can be resolved if Online Review Portals added questions targeted explicitly to those Aspects of the Visitors' Experience in addition to the Open-Ended forms.

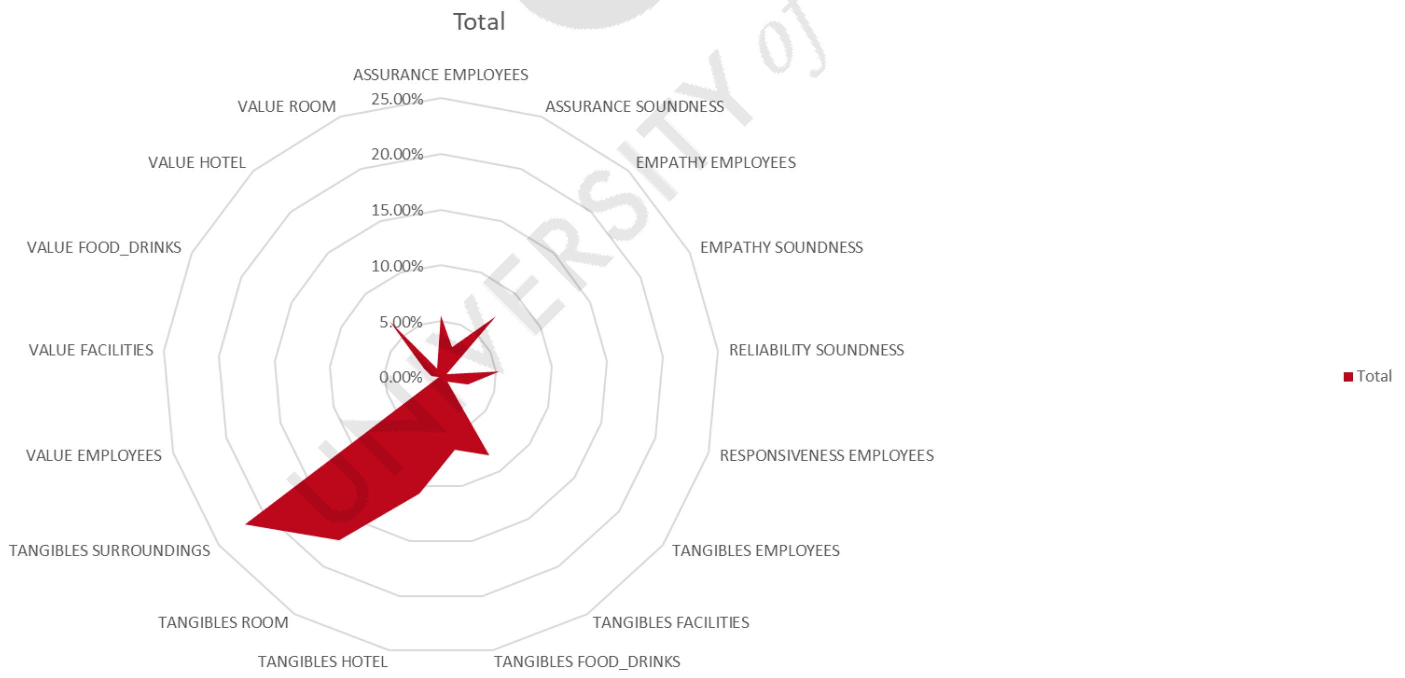



**FIGURE 18 MOST DISCUSSED DIMENSIONS**

The next figure (fig. 19) emerges from the previous diagram if SURROUNDINGS AND ROOM are removed. In this way, the importance of the rest aspects is revealed. As can be seen, HOTEL, FoodnDrinks and Facilities from Tangbiles and Hotel's Value, are among the most discussed categories.

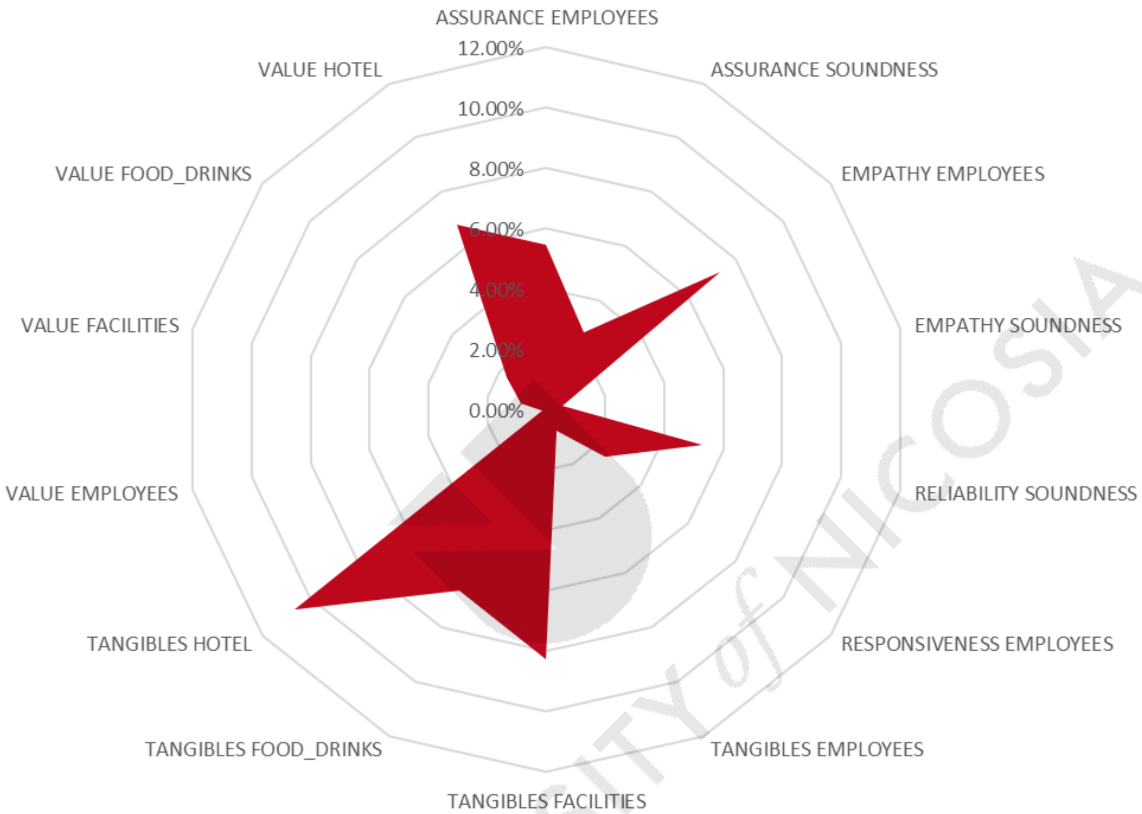



**FIGURE 19 MOST DISCUSSED DIMNEIONS (WITHOUT SURROUNDINGS AND ROOM)**

The following diagram (fig. 20) presents the upper-level dimensions from the perspective of the Intangibles. It is apparent that Empathy, Assurance and Reliability are the more Discussed Topics with the Responsiveness of Employees the least discussed.

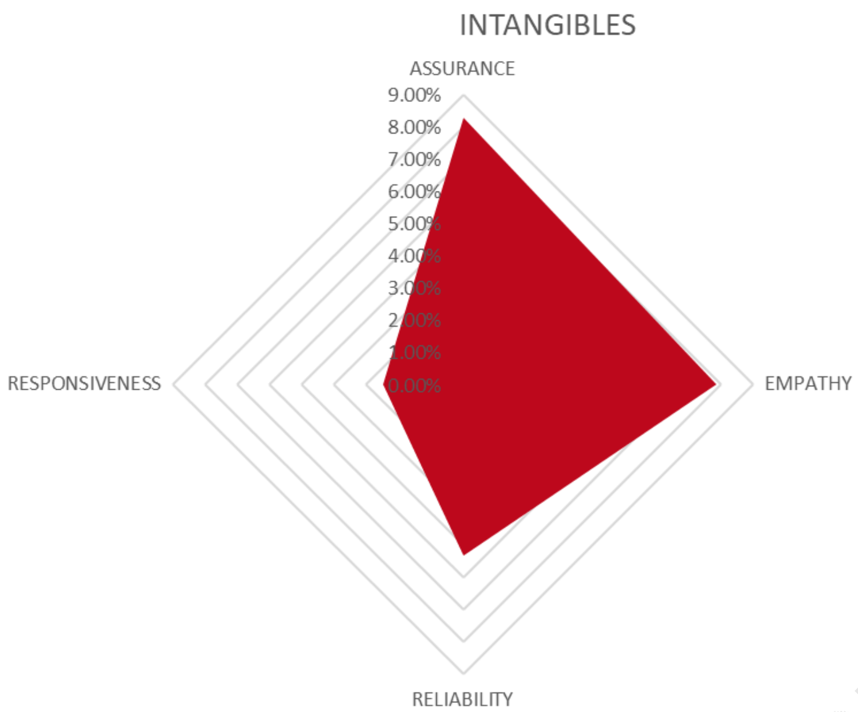



Figure 20 Mid-Level Discussed Intangible Dimensions

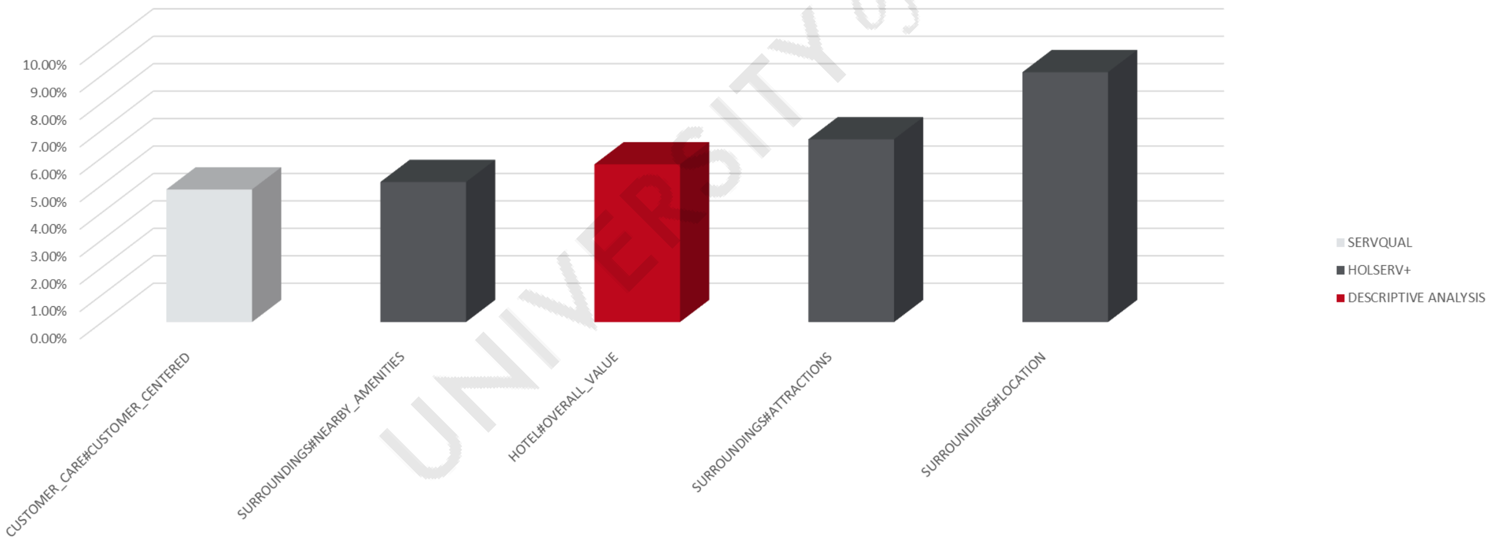



**FIGURE 21 TOP 5 DISCUSSED DIMENIONS INCLUDING DESCRIPTIVE ANALYSIS, SERVQUAL AND HOLSERV**

The top 5 dimensions (fig. 21) discussed are SURROUNDINGS#LOCATION, SURROUNDINGS#ATTRACTIONS, HOTEL#OVERALL_VALUE, SURROUNDINGS#NEARBY_AMENITIES, and CUSTOMER_CARE#CUSTOMER_CENTERED cover 35.79% of the total reviews. In other words, from the 684,284 sentences, 244,909 were related to these six dimensions.

The lowest five dimensions (fig. 22) are ROOM#PRICES, ROOM_AMENITIES#USER_FRIENDLY, SERVICE#PRICE, CUSTOMER_CARE#SCHEDULE_ACCURACY, which relate to 4,411 sentences.

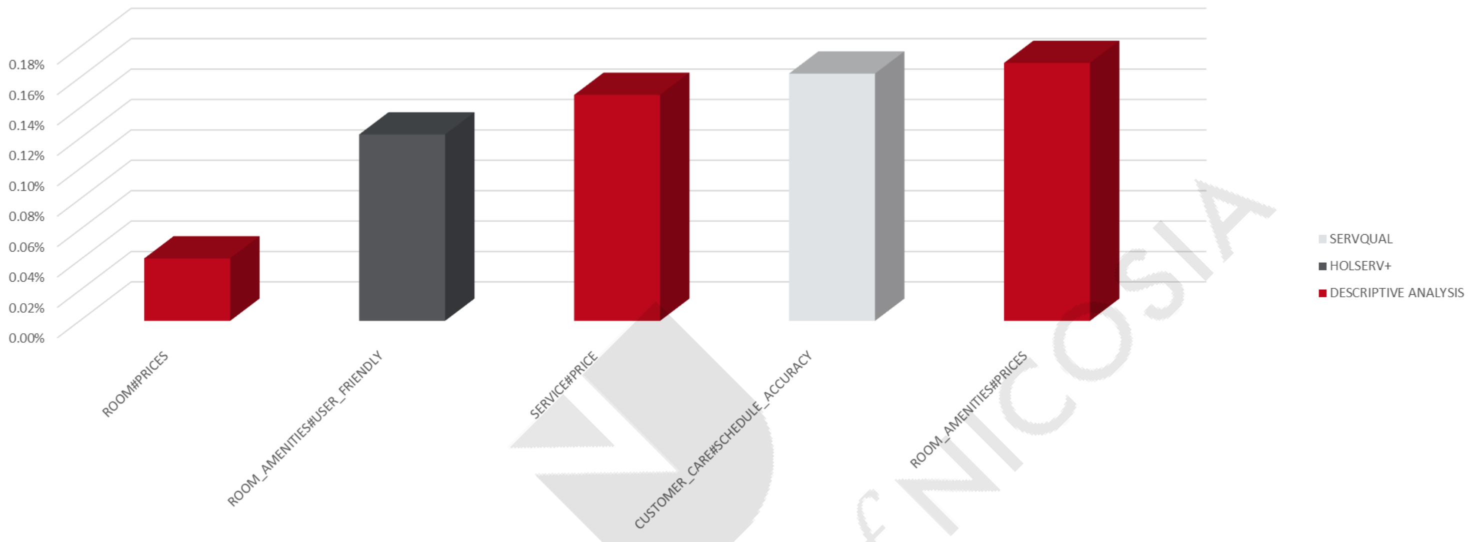



**FIGURE 22 BOTTOM 5 DISCUSSED DIMENIONS INCLUDING DESCRIPTIVE ANALYSIS, SERVQUAL AND HOLSERV**

Also, the 25 lowest dimensions are each under 1% of the total dimensions discussed, and they cover 13.11% or 89,717 of the total sentences. The rest 25 dimensions cover 51.10% of the total categories discussed in reviews, which are 89,707 sentences.

| Table 17 ENHANCED CATEGORIZATION (Sorted by Frequencies) | | ASPECT | | |
|---|---|---|---|---|
| **DIMENSION** | **RELATION** | **ROOM** | **Count** | **Percentage** |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#LOCATION | 62,317.00 | 9.107% |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#ATTRACTIONS | 45,580.00 | 6.661% |
| VALUE | DESCRIPTIVE ANALYSIS | HOTEL#OVERALL_VALUE | 39,345.00 | 5.750% |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#NEARBY_AMENITIES | 34,931.00 | 5.105% |
| EMPATHY | HOLSERV | CUSTOMER_CARE#CUSTOMER_CENTERED | 33,072.00 | 4.833% |
| TANGIBLES | HOLSERV+ | ROOM_AMENITIES#EQUIPMENT | 29,664.00 | 4.335% |
| ASSURANCE | HOLSERV | CUSTOMER_CARE#COURTEOUS | 26,606.00 | 3.888% |
| RELIABILITY | HOLSERV | SOUNDNESS#RECOMMENDABLE | 23,818.00 | 3.481% |
| TANGIBLES | HOLSERV | FACILITIES#DESIGN_FEATURES | 22,886.00 | 3.345% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#QUALITY | 19,821.00 | 2.897% |
| TANGIBLES | HOLSERV+ | ROOM#CLEANLINESS | 17,409.00 | 2.544% |
| TANGIBLES | HOLSERV+ | ROOM#COMFORT | 17,186.00 | 2.512% |
| TANGIBLES | HOLSERV+ | FOOD_DRINKS#STYLE_OPTIONS | 17,170.00 | 2.509% |
| EMPATHY | SERVQUAL, HOLSERV | CUSTOMER_CARE#UNDERSTANDING_SPECIAL_NEEDS | 17,064.00 | 2.494% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FOOD_DRINKS#OVERALL_VALUE | 16,697.00 | 2.440% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#GUEST_CUSTOMIZED | 15,003.00 | 2.193% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FACILITIES#QUALITY | 14,208.00 | 2.076% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FACILITIES#COMFORT | 12,972.00 | 1.896% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#AMBIANCE | 11,993.00 | 1.753% |
| TANGIBLES | HOLSERV+ | FOOD_DRINKS#QUALITY | 11,710.00 | 1.711% |
| VALUE | DESCRIPTIVE ANALYSIS | FOOD_DRINKS#PRICES | 11,646.00 | 1.702% |

| | | | | |
|---|---|---|---|---|
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#COMFORT | 11,201.00 | 1.637% |
| ASSURANCE | SERVQUAL, HOLSERV | CUSTOMER_CARE#KNOWLEDGABLE_and_SKILLFUL | 10,840.00 | 1.584% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | BATHROOM#SIZE | 10,368.00 | 1.515% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#FURNITURE | 10,309.00 | 1.507% |
| ASSURANCE | SERVQUAL, HOLSERV | SOUNDNESS#INSTILLING_CONFIDENCE | 9,437.00 | 1.379% |
| RESPONSIVENESS | SERVQUAL, HOLSERV | CUSTOMER_CARE#PROMPTNESS | 9,367.00 | 1.369% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | BATHROOM#CLEANLINESS | 8,614.00 | 1.259% |
| TANGIBLES | SERVQUAL, HOLSERV | HOTEL#DESIGN_FEATURES | 8,115.00 | 1.186% |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#TRANSPORT | 7,972.00 | 1.165% |
| VALUE | DESCRIPTIVE ANALYSIS | HOTEL#PRICES | 7,256.00 | 1.060% |
| RELIABILITY | SERVQUAL, HOLSERV | SOUNDNESS#PROBLEM_ADMINISTRATION | 6,691.00 | 0.978% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#CLEANLINESS | 6,628.00 | 0.969% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FACILITIES#CLEANLINESS | 6,584.00 | 0.962% |
| RESPONSIVENESS | SERVQUAL, HOLSERV | CUSTOMER_CARE#EAGERNESS | 6,562.00 | 0.959% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM_AMENITIES#BED_COMFORT | 6,193.00 | 0.905% |
| ASSURANCE | SERVQUAL, HOLSERV | SOUNDNESS#SECURITY | 6,181.00 | 0.903% |
| VALUE | DESCRIPTIVE ANALYSIS | FACILITIES#PRICES | 5,855.00 | 0.856% |
| TANGIBLES | SERVQUAL, HOLSERV | ROOM#DESIGN_FEATURES | 5,226.00 | 0.764% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#SIZE | 4,750.00 | 0.694% |
| VALUE | DESCRIPTIVE ANALYSIS | ROOM#OVERALL_VALUE | 4,512.00 | 0.659% |
| TANGIBLES | SERVQUAL, HOLSERV | SERVICE#CLEANLINESS | 3,908.00 | 0.571% |
| EMPATHY | SERVQUAL, HOLSERV | SOUNDNESS#CONVENIENT_OPERATING_HOURS | 3,768.00 | 0.551% |
| ASSURANCE | SERVQUAL, HOLSERV | SOUNDNESS#WITHOUT_MISTAKES | 3,677.00 | 0.537% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM_AMENITIES#QUALITY | 3,188.00 | 0.466% |

| | | | | |
|---|---|---|---|---|
| RELIABILITY | SERVQUAL, HOLSERV | SOUNDNESS#SERVICE_ON_TIME_WHEN_PROMISED | 3,120.00 | 0.456% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | BATHROOM#EQUIPMENT | 2,997.00 | 0.438% |
| TANGIBLES | SERVQUAL, HOLSERV | SERVICE#APPEARANCE | 1,417.00 | 0.207% |
| RELIABILITY | SERVQUAL, HOLSERV | SOUNDNESS#EFFICIENCY | 1,405.00 | 0.205% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#INTERNET | 1,366.00 | 0.200% |
| RELIABILITY | DESCRIPTIVE ANALYSIS | SOUNDNESS#MANAGEMENT | 1,268.00 | 0.185% |
| VALUE | DESCRIPTIVE ANALYSIS | ROOM_AMENITIES#PRICES | 1,161.00 | 0.170% |
| RESPONSIVENESS | SERVQUAL, HOLSERV | CUSTOMER_CARE#SCHEDULE_ACCURACY | 1,113.00 | 0.163% |
| VALUE | DESCRIPTIVE ANALYSIS | SERVICE#PRICE | 1,017.00 | 0.149% |
| TANGIBLES | HOLSERV+ | ROOM_AMENITIES#USER_FRIENDLY | 839.00 | 0.123% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#PRICES | 281.00 | 0.041% |
| | | **TOTAL** | **684,284** | **100%** |

Table 18. presents only the SERVQUAL scale related dimensions. The number of annotated sentences explained from SERVQUAL is 161,508. This is 29.85% of the total number of the sentences that is 204,273. CUSTOMER_CARE#CUSTOMER_CENTERED is the dimensions most used from the reviewers when it comes to the SERVQUAL scale, with 33,072 related sentences and 4.83% of the total sentences. The top 5 sub-dimensions represent 60.43% of the total SERVQUAL dimensions. The least represented categories were the CUSTOMER_CARE#SCHEDULE_ACCURACY with only 1,113 related sentences, SOUNDNESS#EFFICIENCY with 1,405 sentences, and SERVICE#APPEARANCE with 1,417 sentences. The specific sentences are related to Responsiveness, Reliability, and Tangibles SERVQUAL dimensions.

| Table 18 ENHANCED CATEGORIZATION (SERVQUAL) | | ASPECT | | |
|---|---|---|---|---|
| **DIMENSION** | **RELATION** | **ROOM** | **Count** | **Percentage** |
| TANGIBLES | SERVQUAL | ROOM#DESIGN_FEATURES | 5,226 | 0.764% |
| TANGIBLES | SERVQUAL | HOTEL#DESIGN_FEATURES | 8,115 | 1.186% |
| TANGIBLES | SERVQUAL | FACILITIES#DESIGN_FEATURES | 22,886 | 3.345% |
| TANGIBLES | SERVQUAL | SERVICE#APPEARANCE | 1,417 | 0.207% |
| TANGIBLES | SERVQUAL | SERVICE#CLEANLINESS | 3,908 | 0.571% |
| RESPONSIVENESS | SERVQUAL | CUSTOMER_CARE#SCHEDULE_ACCURACY | 1,113 | 0.163% |
| RESPONSIVENESS | SERVQUAL | CUSTOMER_CARE#PROMPTNESS | 9,367 | 1.369% |
| RESPONSIVENESS | SERVQUAL | CUSTOMER_CARE#EAGERNESS | 6,562 | 0.959% |
| ASSURANCE | SERVQUAL | CUSTOMER_CARE#COURTEOUS | 26,606 | 3.888% |
| ASSURANCE | SERVQUAL | CUSTOMER_CARE#KNOWLEDGABLE_and_SKILLFUL | 10,840 | 1.584% |
| EMPATHY | SERVQUAL | CUSTOMER_CARE#CUSTOMER_CENTERED | 33,072 | 4.833% |
| EMPATHY | SERVQUAL | CUSTOMER_CARE#UNDERSTANDING_SPECIAL_NEEDS | 17,064 | 2.494% |
| EMPATHY | SERVQUAL | SOUNDNESS#CONVENIENT_OPERATING_HOURS | 3,768 | 0.551% |
| RELIABILITY | SERVQUAL | SOUNDNESS#SERVICE_ON_TIME_WHEN_PROMISED | 3,120 | 0.456% |
| RELIABILITY | SERVQUAL | SOUNDNESS#EFFICIENCY | 1,405 | 0.205% |
| RELIABILITY | SERVQUAL | SOUNDNESS#PROBLEM_ADMINISTRATION | 6,691 | 0.978% |
| RELIABILITY | SERVQUAL | SOUNDNESS#RECOMMENDABLE | 23,818 | 3.481% |
| ASSURANCE | SERVQUAL | SOUNDNESS#WITHOUT_MISTAKES | 3,677 | 0.537% |
| ASSURANCE | SERVQUAL | SOUNDNESS#INSTILLING_CONFIDENCE | 9,437 | 1.379% |
| ASSURANCE | SERVQUAL | SOUNDNESS#SECURITY | 6,181 | 0.903% |
| | | **TOTAL** | **161,608** | **29.852%** |

Table 20. presents results related to the HOLSERV+ dimensions. This analysis is far more detailed than the original HOLSERV+ suggested model. The initial model suggested only the basic dimensions of Tangibles (Room, Facilities, Surroundings), Reliability and Employees (seen in the HOLSERV scale above). So, there are only five dimensions in total. The HOLSERV+ dimensions presented below are related to the categories taken into account by the HOLSERV+ model to create those five dimensions.

Table 19 HOLERV and HOLSERV+ Dimensions

| **HOLSERV** | **HOLSERV+** |
|---|---|
| tangibles | room, facilities, surroundings |
| reliability | reliability |
| employees | employees |

Given the following results, most of the HOLSERV+ dimensions are correlated to the upper quartile of the total dimensions. This seems reasonable, given that HOLSERV+ dimensions were developed from an analysis of the online reviews. The dimension with the lowest number of related sentences are ROOM_AMENITIES#USER_FRIENDLY, with just 839 related sentences. All the other dimensions belong to the upper 25 dimensions of the suggested enhanced model.

| Table 20. ENHANCED CATEGORIZATION (HOLERV+) | | ASPECT | | |
|---|---|---|---|---|
| RELATION | RELATION | ROOM, FACILITIES, SURROUNDINGS | Count | Percentage |
| TANGIBLES | HOLSERV+ | ROOM#CLEANLINESS | 7,621 | 1.114% |
| TANGIBLES | HOLSERV+ | ROOM#COMFORT | 15,094 | 2.206% |
| TANGIBLES | HOLSERV+ | ROOM_AMENITIES#USER_FRIENDLY | 2,127 | 0.311% |
| TANGIBLES | HOLSERV+ | ROOM_AMENITIES#EQUIPMENT | 6,045 | 0.883% |
| TANGIBLES | HOLERV+ | FACILITIES#MISCELLANEOUS | 23,997 | 3.507% |
| TANGIBLES | HOLSERV+ | FOOD_DRINKS#STYLE_OPTIONS | 22,200 | 3.244% |
| TANGIBLES | HOLSERV+ | FOOD_DRINKS#QUALITY | 15,351 | 2.243% |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#LOCATION | 69,817 | 10.203% |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#NEARBY_AMENITIES | 58,448 | 8.541% |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#TRANSPORT | 8,667 | 1.267% |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#ATTRACTIONS | 38,954 | 5.693% |
| | | TOTAL | **268,321** | **39.212%** |

When it comes to Descriptive Analysis dimensions (Table 21), they cover 34.38% of the total dimensions discussed by reviewers. This means that the newly added dimensions improve the initial SERVQUAL and HOLSERV(+) model considerably, providing more depth to understanding visitors' experiences.

In more detail, HOTEL#OVERALL_VALUE is the most frequent dimension appearing in the review sentences, with 39,345 counts and 5,75% of the reviewed text. It also covers 16,73% of the overall descriptive analysis dimensions. The category HOTEL#GUEST_CUSTOMIZED which is related to accommodation that is customized to visitors needs (family hotel, business hotel, and more), has received 15,003.00 references, which represents 2,19% of the total sentences. Also, HOTEL#AMBIANCE has been discussed in 11,993 sentences or 1.75% of the total.

SOUNDNESS#MANAGEMENT, which is related to the accommodation's management behaviour and decisions, is one of the least referred categories with a frequency of 1,268.00, that is 0,18% of the studied corpus. The least frequent dimensions are the ROOM_AMENITIES#PRICES, SERVICE#PRICE, ROOM#PRICES with 1,261, 1,017, and 281 counts, respectively.

| Table 21 ENHANCED CATEGORIZATION | | ASPECT | | |
|---|---|---|---|---|
| | | | | |
| **RELATION** | **RELATION** | **ROOM** | **Count** | **Percentage** |
| VALUE | DESCRIPTIVE ANALYSIS | ROOM_AMENITIES#PRICES | 1,161.00 | 0.170% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM_AMENITIES#QUALITY | 3,188.00 | 0.466% |
| VALUE | DESCRIPTIVE ANALYSIS | ROOM#OVERALL_VALUE | 4,512.00 | 0.659% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#PRICES | 281.00 | 0.041% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#INTERNET | 1,366.00 | 0.200% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM_AMENITIES#BED_COMFORT | 6,193.00 | 0.905% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#SIZE | 4,750.00 | 0.694% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#FURNITURE | 10,309.00 | 1.507% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | BATHROOM#CLEANLINESS | 8,614.00 | 1.259% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | BATHROOM#EQUIPMENT | 2,997.00 | 0.438% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | BATHROOM#SIZE | 10,368.00 | 1.515% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#GUEST_CUSTOMIZED | 15,003.00 | 2.193% |
| VALUE | DESCRIPTIVE ANALYSIS | HOTEL#PRICES | 7,256.00 | 1.060% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#QUALITY | 19,821.00 | 2.897% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#COMFORT | 11,201.00 | 1.637% |
| VALUE | DESCRIPTIVE ANALYSIS | HOTEL#OVERALL_VALUE | 39,345.00 | 5.750% |

| | | | | |
|---|---|---|---|---|
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#CLEANLINESS | 6,628.00 | 0.969% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#AMBIANCE | 11,993.00 | 1.753% |
| VALUE | DESCRIPTIVE ANALYSIS | FACILITIES#PRICES | 5,855.00 | 0.856% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FACILITIES#QUALITY | 14,208.00 | 2.076% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FACILITIES#COMFORT | 12,972.00 | 1.896% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FACILITIES#CLEANLINESS | 6,584.00 | 0.962% |
| VALUE | DESCRIPTIVE ANALYSIS | FOOD_DRINKS#PRICES | 11,646.00 | 1.702% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FOOD_DRINKS#OVERALL_VALUE | 16,697.00 | 2.440% |
| VALUE | DESCRIPTIVE ANALYSIS | SERVICE#PRICE | 1,017.00 | 0.149% |
| RELIABILITY | DESCRIPTIVE ANALYSIS | SOUNDNESS#MANAGEMENT | 1,268.00 | 0.185% |
| | | **TOTAL** | **235,233** | **34.377%** |

The results mentioned above do not mean that the lowest frequency categories are less significant. Instead, these categories are part of larger categorisations broken down to more specific areas. So, in general, Value has a frequency of 60,554 related sentences, appearing in the dimensions ROOM#OVERALL_VALUE, HOTEL#OVERALL_VALUE, FOOD_DRINKS#OVERALL_VALUE. Additionally, Prices included in ROOM#PRICES, ROOM_AMENITIES#PRICES, HOTEL#PRICES, FOOD_DRINKS#PRICES, SERVICE#PRICE are discussed in 27,216 sentences, that is 3,98% of the descriptive analysis dimensions. Comfort, which is split down to ROOM_AMENITIES#BED_COMFORT, ROOM_AMENITIES#BED_COMFORT, HOTEL#COMFORT, FACILITIES#COMFORT, counts for 30,366 4.44% of 12.91% of the total descriptive dimensions. Quality includes ROOM_AMENITIES#QUALITY, HOTEL#QUALITY, FACILITIES#QUALITY, which have a 37,217 frequency, that is, 15,82% of the total descriptive dimensions. Cleanliness, which sum ups to 9.28% of the total descriptive dimensions, has 21,826 records and consists of BATHROOM#CLEANLINESS, HOTEL#CLEANLINESS, FACILITIES#CLEANLINESS (Table 22.)

Finally, in research Overall Value and Price can also be conceived as one dimension named Value. In this case, Value's frequency is 87,770, which is 37.31% of the total descriptive dimensions and 12.83% of the enhanced model's total dimensions. This adds to the significance of these categories in the enhanced model dimensions.

Table 22 ENHANCED CATEGORIZATION (Sub-Categories)

| Category | Count | Percentage |
|---|---|---|
| OVERALL_VALUE | 60,554 | 8.85% |
| PRICE | 27,216 | 3.98% |
| COMFORT | 30,366 | 4.44% |
| QUALITY | 37,217 | 5.44% |
| CLEANLINESS | 21,826 | 3.19% |
| **TOTAL** | 177,179 | 25.89% |

Tables 23, 24, 25, provide the three groupings of the model's dimensions, which, together with Table 17, provide an overview of the 4 group dimensions that can provide differentiated information on the online reviews. Additionally, to these groupings, we have individual subgroups that can expand the view and understanding of the reviews as well. The subgroups discussed are Overall Value, Price, Comfort, Quality and, Customer_Centered (which includes EMPLOYEES#INDIVIDUAL ATTENTION, EMPLOYEES#CARING, EMPLOYEES#CUSTOMER_CENTERED), EMPLOYEES (EMPLOYEES#CUSTOMER_CARE, EMPLOYEES#SERVICE), and Room (which includes ROOM, ROOM_AMENITIES and, BATHROOM).

In Table 17, the most under-represented category is EMPLOYEES#SERVICE, which represents just 0.93% of the total annotated sentences. The categories SURROUNDINGS and HOTEL are the most discussed categories.

| TABLE 23 ENCHANCE CATEGORIZATION (GROUP 1) | | |
|---|---|---|
| **Dimensions** | **Count** | **Percentage** |
| TANGIBLES | 520,295.00 | 76.03% |
| INTANGIBLES | 163,989.00 | 23.97% |
| **TOTAL** | 684,284 | 100.00% |

| TABLE 24 ENCHANCED CATEGORIZATION (GROUP 2) | | |
|---|---|---|
| TANGIBLES | 450,383 | 65.82% |
| VALUE | 69,912 | 10.22% |
| RELIABILITY | 36,302 | 5.31% |
| RESPONSIVENESS | 17,042 | 2.49% |
| ASSURANCE | 56,741 | 8.29% |
| EMPATHY | 53,904 | 7.88% |
| **TOTAL** | 684,284 | 100.00% |

| **TABLE 25. ENCHANCED CATEGORIZATION** (Group 3) | | |
|---|---|---|
| **Dimensions** | **Count** | **Percentage** |
| ROOM | 61,039 | 8.92% |
| ROOM_AMENITIES | 41,045 | 6.00% |
| BATHROOM | 21,979 | 3.21% |
| HOTEL | 119,362 | 17.44% |
| SURROUNDINGS | 150,800 | 22.04% |
| FACILITIES | 62,505 | 9.13% |
| FOOD_DRINKS | 57,223 | 8.36% |
| EMPLOYEES#CUSTOMER_CARE | 104,624 | 15.29% |
| EMPLOYEES#SERVICE | 6,342 | 0.93% |
| SOUNDNESS | 59,365 | 8.68% |
| **TOTAL** | 684,284 | 100.00% |



The subgroup ROOM, ROOM_AMENITIES, and BATHROOM brings the ROOM category above HOTEL category, with 124,063 sentences discussing this dimension. Additionally, if we sum up the Employees dimension (EMPLOYEES#CUSTOMER_CARE, EMPLOYEES#SERVICE), the EMPLOYEES category counts 110,966. In TABLE 16, where the TANGIBLES dimension is grouped up, RESPONSIVENESS is the least discussed dimension, with only 17,042 sentences related to this category, followed by RELIABILITY, with 36,302 instances of the category in reviews. The most discussed dimension is TANGIBLES, which represents 65,82% of the total discussed dimensions. The second most discussed dimension is VALUE, with 10% of the total, which shows the importance of customers' value and price. In TABLE 16, the TANGIBLES category represents 76,03% of the total discussed sentences, and the INTANGIBLES category is only 23,97% of the total sentences discussed. Finally, in Table 26, the subcategories OVERALL VALUE, PRICE, COMFORT, QUALITY, and CLEANLINESS are summed up, representing 25.89% of the discussed topics. In this Table, the least discussed dimension is Cleanliness, which is 3.39% with the most discussed categories Overall, Value, and Price. Comfort and Quality also seem important parameters for reviewers since they are 4,44% and 5,44%, respectively.

| **TABLE 26 Sub-Categories** Frequencies | | |
|---|---|---|
| **Category** | **Count** | **Percentage** |
| OVERALL_VALUE | 60,554 | 8.85% |
| PRICE | 27,216 | 3.98% |
| COMFORT | 30,366 | 4.44% |
| QULAITY | 37,217 | 5.44% |
| CLEANLINESS | 21,826 | 3.19% |
| **TOTAL** | 177,179 | 25.89% |

### 4.3.4 Discussion

The second study provides a framework that can be used to extract and annotate online reviews into topics discussed in online reviews. Machine learning algorithms and deep neural networks can provide the possibility for researchers to have an in-depth look into online reviews by incorporating the wisdom provided b y scales used only in questionnaires before. Additionally, the model can be used by adding the results from SERVQUAL (or other) surveys to the results of an aspect classification analysis of online reviews and combine both results into tables and analytics. This can give an overview and an analytical view of the data, which was not possible before.

Previous research was able to produce an one-dimensional matching only the upper-level HOLSERV categories (Boon, Bonera and Bigi, 2014); therefore, this research's first goal has been to develop a model and an approach that would include the upper-level categories of service quality scales, but also mid-level and low-level categorization. The thesis' initial model achieved in including both the SERVQUAL dimensions and the HOLSERV(+) dimensions. The deep neural network algorithm produced class categorisation for both models (initial and final proposed model) and shows among others, that it is possible to bring the SERVQUAL/HOLSERV dimensions and categorisation into online reviews. Based on the aspect analysis, we understand that survey instruments can have a valuable role in big data analytics. Specifically, the results show that it is possible to match the aspects of sentences to the quality assessment survey dimensions.

In this model, the total amount of SERVQUAL/HOLSERV dimensions in relation to the total number of sentences is 286,158 or 46.62% of the reviewed sentences. This means that SERVQUAL/HOLSERV dimensions are an essential part when it comes to online reviews. Nevertheless, in SERVQUAL table, ten categories are under 5,500 counts, or, in other words, they are under 1% of the total annotated sentences.

The frequency analysis revealed that specific dimensions are not included in the SERVQUAL and HOLSERV but even HOLSERV+ model. Overall value and price belong to these categories. Overall value turned out to be the most prominent dimension among the descriptive analysis introduced categories, covering 16,73% of the overall descriptive dimensions results. The others are quality, comfort, guest customized hotel, hotel ambiance, bathroom details. The enhanced multi-dimension model analysis shows that these categories are essential aspects for the reviewers. Specifically, the dimensions related to the descriptive analysis explain 34.38% of the total corpus. A suggestion derived from these results is that survey quality assessment tools could be updated with current customers' quality requirements to include dimensions like overall value, price, internet, and comfort. Based on all models, the initial model, and the final proposed model, there are dimensions that cover a significant part of quality assessment scales that are not discussed in the open-ended forms provided to online reviewers to describe their experiences. Some of the SERVQUAL dimensions, which are under-represented in online reviews, are EMPLOYEES#SCHEDULE_ACCURACY, EMPLOYEES#CARING, EMPLOYEES#INDIVIDUAL ATTENTION. Additionally, the intangibles dimension is generally less represented in online reviews, since it is just 23.97% of the studied corpus. Therefore, it could be difficult for researchers and professionals or individuals seeking such information in smaller samples, to locate relevant information in online reviews. One reason might be that online reviews mainly provide open-ended questions to reviewers (i.e., how was your stay?), which allow the visitor to express their experience concerning their stay. This can be aleviated, for instance, by having an algorithm running on the background matching the review sentences to the suggested model's dimensions. When the model finds some dimension deficiency, it can add a couple of questions targeted to the missing dimensions, so that each review provides a better picture of the visitor's experience. Otherwise, as seen from the stage of the manual training dataset annotation stage, reviews collected from a small number of accommodation units can hardly cover the basic service quality assessment dimensions. Consequently, online Organizations (i.e., Travel agencies, online wholesalers and retailers, social media like Facebook, Fursquare) as well as providers of live assessment systems (i.e., ReviewPro, TrustYou, Revinate), can re-arrange the way the review forms are given and filled. These rearrangements can be made in ways that provide more valuable information for any interested party, whether they are researchers, consumers, private sector, or other organisations. Nevertheless, the model can be used even without changes in the current ways of collecting online reviews.

The suggested model can be used as a systematic and universal way to measure/identify dimensions. The model is fully customizable (by customizing the training dataset), based on the analysis researched dimensions. Therefore, it can classify unstructured text (i.e., online reviews, travel blog reviews) into quality assessment dimensions used in surveys (i.e., SERVQUAL, HOLSERV, LODGSERV, HOTELQUAL, HISTOQUAL, AUTOQUAL, ECOSERV). In this way, quality assessment tools are combined, providing more information in one easier accessible and studied form. In addition to the ability of combining information from different sources, the model provides a robust way to study the changes of dimensions in time. This can be done by categorizing the results based on the month or year the reviews were written in and studying the changes in customer quality needs and/or provided quality over time.

Moreover, through this enhanced multi-dimensional model, four groups of dimensions and five subgroups have been developed, which on the one hand, can provide an overview of the discussed dimensions as well as a reasonably detailed view of the dimensions discussed in online reviews. Moreover, all dimensions and subdimensions can be viewed individually or as a group. For example, even the 'equipment', 'cleanliness', and 'comfort' can be viewed in groups. Consequently, an additional advantage of this study is that it offers a multi-dimensional model that enables researchers to study and combine surveys with the information provided by online reviews. At the same time, the model allows for researchers to be able to approach online reviews from five different dimensional groups/angles from macro (intangibles-tangibles), meso ((TANBIBLES, VALUE, RELIABILITY, RESPONSIVENESS, ASSURANCE, EMPATHY) or (ROOM, ROOM_AMENITIES and more)) and micro-levels (ROOM#CLEANLINESS, ROOM#COMFORT and more). The fifth-dimensional group contains the grouping of cleanliness, comfort, quality, price, and value, which sum-up characteristics of the experience from Hotel, Facilities, Room, and Bathroom as a whole. In parallel, both professionals from the private and public sectors, and individuals searching for specific information, can now obtain advanced analytics based on this model. The model can provide them with the exact information they are seeking.

The present Thesis can be of benefit to researchers and both private and public sector professionals who, can gain valuable insight into service quality. By gaining a better understanding of the travellers' expectations and preferences, they could restructure their services and products accordingly in ways that better satisfy the consumers.

# CHAPTER 5 CONCLUSIONS AND DIRECTIONS FOR FUTURE DEVELOPMENT

## 5.1. INTRODUCTION

The first section of this Chapter discusses the resulting conclusions of this Thesis. The second section focuses on the Thesis' limitation of each study and suggests future areas of further expanding the results of this research.

## 5.2. CONCLUSIONS

The first part of this thesis investigates hotel owners and managers' opinions in Crete in relation to quality assessment methods of surveys and online reviews. The results of this study show that all the interview participants use online reviews to get updates on visitors' accommodation experiences. TripAdvisor has been the most used travel portal for viewing, analyzing, and responding to online reviews. The second most used has been Booking.com. Online reviews have been acting as a marketing tool, improving the hotel's image and presence in the hospitality accommodation market, and as a result, attracting more clients.

Moreover, online reviews have been a valuable tool for accommodation providers, to translate the increasing attention and ratings from reviewers to achieve raises in next season's prices when negotiating with tour operators. More than half of these respondents use both surveys and online reviews for their enlightenment. Nevertheless, they are divided when it comes to whether one of the tools or a combination of both provides more complete information.

There are certain advantages to each tool. Surveys usually take place during the visitor's stay. This allows, hotel management to respond and provide solutions to potential problems. As a consequence, surveys can act as a tool to improve the visitor's experience and make their stay more pleasant. A more pleasant experience is usually also translated to better reviews and ratings. Consequently, it might be beneficial for every party involved, if tourism stakeholders encouraged travellers to give a first evaluation concurrently with their experience.

Additionally, quality assessment scales provide a wide range of topics while reviews are rarely so detailed to cover all possible topics. Furthermore, these scales can be customized to return information on each hotel's specific quality goals. Finally, the close-ended nature of quality surveys makes it easier for hotel managers to analyze them all together and get results.

On the other hand, online reviews provide accommodation providers with the option to further contact visitors regarding their comments. Online reviews are considered trustworthy and effective tools. According to the respondents, any reliability issues can be overcome by crosschecking the reviews, which is already a task of the accommodation representative. As opposed to surveys with close-ended questions, online reviews offer open questions and might therefore provide additional service quality information that surveys do not cover. These findings lead us to infer that each tool's unique aspects cannot be overlapped with one another. Both tools are essential and useful in the quality assessment process. Nevertheless, the benefits can be multiplied if the information can be combined in a way that is easily navigable and comprehensive.

The proposed model developed from the thesis can be used from (Inter)National Organizations and Accommodation Providers to have a multi-angle view of the Quality Provided through their Services, from an Overview to detailed groupings of a variety of aspects. Moreover, the model can be combined with the results from Quality Assessment Scales that Managers use inHouse, by just dropping the results of their Scales in the Proposed Model's DataSet, and getting a better overview as well as a more detailed picture of their Quality Service Results. Incorporating the proposed model's categorization to Online Review Portal systems will allow these Portals to provide precise and more insightful Analytics to both Managers and prospective Travelers. The ability to view the results from multiple angles aids Managers to better understand their strengths and weaknesses, and build on them their Strategies. Also, Destination Image Developers can have a more precise understanding of visitors' needs and achieve better oriented Marketing Campaigns.

From a theoretical point of view, this is the first research to investigate the possibility of classifying Online Reviews into all the dimensions and sub-dimensions of Quality Assessment Scales. Previous research has managed to fit only upper-level dimensions like Tangibles, Reliability, Responsiveness etc. Moreover, the Dimensions risen from Descriptive Analysis, cover 34.38% of the total dimensions discussed from reviewers. This means that the newly added dimensions improve the initial SERVQUAL AND HOLSERV(+) model considerably, providing more depth in our understanding of the visitors' experiences. The 5 Groups of different level Dimensions, that this research introduced, Provide the Ability to Study from a variety of angles the reviewers' perceived experiences. The study transforms Online Reviews into a Dataset of Categories which is fully compatible with Quality Assessment Scales.

From a systemic point of view, the thesis introduces a novel Corpus Training Annotation process that can be used in order to obtain and process more analytical classifications. The annotation process follows Almagrabi, Malibari and Mcnaught's (2018) approach regarding corpus analysis with the scheme approach of ABSA (Pontiki et al. 2014, 2016). This corpus training annotation process, combined with the novel categorization, can be used to obtain and process more analytical classifications.

The proposed multi-dimensional model provides a standardized way to present and study quality dimensions. Specifically, four groups of dimensions and five subgroups have been developed. All the dimensions and subdimensions can be viewed individually or as a group. For example, even the equipment, cleanliness, and comfort subgroups can be viewed in groups. Therefore, this model's approach can provide an overview as well as an in-depth view of the discussed topics in online reviews. The proposed Model is fully customizable and can be applied to reviews from portals like Museums, Commercial Stores like Amazon and any portal that entails User Generated Content. Also, as discussed earlier, with a simple code matching of survey questionnaires, the survey results can be transformed into the model's dimensions. In this way, both information sources (surveys and unstructured text) can be aggregated to provide even more powerful and insightful analytics.

This thesis proposes a new framework for processing and categorizing unstructured information (in this case online reviews), into prespecified categorization (i.e. the initial quality assessment scales of SERVQUAL and HOLSERV(+) in this thesis). The framework also utilizes deep neural networks and incorporates the seed-based aspect-classification methodology; moreover, the annotation approach makes the development of the machine learning algorithm's training corpus possible. The framework includes a descriptive analysis that uncovers additional dimensions. This methodological approach leads to developing the proposed multi-dimensional model, which can be customized to the interested party's needs. This framework and derived multi-dimensional model can be applied to other fields beyond Tourism, like online or offline stores (i.e., BestBuy, Amazon, eBay), job portals (i.e., Glassdoor, LinkedIn), museums, medical evaluations, and other services. It can be virtually applied to any field that entails assessing a product or service provided that has been evaluated with surveys, and for which also exist unstructured text evaluations (i.e., online reviews, blog reviews, forum discussions).

## 5.3 LIMITATIONS

When it comes to the first study, one contradiction arising through this work is that on one hand, R.C.V. states that they prefer questionnaires because online reviews usually take place a while after the stay, as opposed to surveys that take place while the customer is in the hotel (S.B.C.R.S.). This means that the memory of customers' experience has fainted (Id.). On the other hand, Ac. and G.C.S. hotels argue that online reviews usually occur after the customers have left the hotel and have the composure to do an objective assessment of their stay. Both situations probably co-exist, and each practice can impact differently on the accommodation provider's ability to assess service quality and respond to the visitor's needs. In this case, one solution could be to encourage visitors to express their feelings and experience during their stay, through an online review or otherwise. From the perspective of critical realism, differentiation in the observations of the actual realm are welcome, because they can create a more complete view of the dynamics of the empirical realm. Knowledge can be realized through different observations and based on various influences and interests, which means that knowledge is context and activity-dependent (Rutzu et al. 2016). Finally, since observations are fallible, pluralism can aid in developing an image of the most persistent observations, which can lead to new inferences about the nature of reality.

A limitation of this research is that it focuses on information from the region of Crete. Crete accommodates many business travellers and is also a highly touristic region of Greece, especially for the summer season, attracting guests from all around the world, providing a cultural diversity of the sample that ensures the study's validity. Nevertheless, additional studies of other regions, of both touristic and non-touristic destinations, would reinforce the model's validity. When it comes to the first study, the information gathered has provided details that allowed useful insights regarding managers perspectives on quality assessment methods. Moreover, it is common ground to conduct qualitative research based on interviews with fifteen or fewer participants. Still, more studies with accommodation providers from different regions will add to this study's validity as well. Additionally, the methodological approach of email interviewing made it challenging to re-approach the participants to ask for additional details. In this study, it was not possible, mainly due to participants' lack of time, to engage either in person or through skype.

The approach to quality assessment processes that review providers have is apparent through the forms and analytics they provide. Nevertheless, it would be interesting to have, through an interview, their perception of quality assessment dimensions, how often they update their forms, if they are interested in adding the dimensions suggested by this study. Unfortunately, although a few attempts have been made to approach a couple of providers (i.e., TripAdvisor, Booking.com), there was no response from their part. Therefore, in the future, it would be interesting to communicate the suggested model to online review providers but also have a view of the background processing they perform, in order to be able to recommend solutions that would fit their already-placed models.

## 5.4 Directions for Future Research

Concerning the research on managers' perceptions on service quality tools, while studying the actions taken based on their quality assessment results, the study investigates the questionnaire quality dimensions found in online reviews. From the five-quality dimensions provided by the SERVQUAL/HOLSERV+ scale, the respondents seem to have realized actions on four of them, that is, Room, Facilities, Employees and Reliability. The respondents did not mention any actions taken towards the Surroundings dimension and there was only one instance out of nine mentioning the Room dimension. Although this might result from the low sample of this qualitative research, it might be interesting future research to investigate more this finding since it might lead to useful inferences concerning both tools.

Moreover, the aforementioned limitations can be transformed into research paths that expand the Thesis and add to this research's validity. In this context, the interview-based research concerning managers' perceptions on service quality tools can be expanded to different regions of the globe. This expansion can lead to a better and more in-depth understanding of how these tools are used their perceptions about their quality and efficiency regarding their businesses. Moreover, expanding the research beyond the field of Tourism can develop a broader understanding of the business world opinions on the quality assessment tools, allowing for a better understanding of how eWOM is received by companies and organisations.

Concerning the data mining study, in the future, it would be interesting to communicate the suggested model to online review providers in addition to having a view of the background processing they perform, in order to be able to recommend solutions that would fit their already-placed models. Most of the online reviews provide a couple of open-ended questions regarding the consumer's experience. These online review forms can be programmed to break down, in real-time, the reviewer's text response, into dimensions. According to the text entered, a couple more questions can then appear regarding dimensions that the reviewer has not touched. In this way, they could keep the advantages of open-ended questions with the completeness of information the questionnaires provide.

Based on this research's findings, we understand that both tools (online reviews and quality assessment scales) add to the quality assessment. This is consistent with Boon, Bonera and Bigi (2013) concluding remarks that online reviews cannot replace traditional service quality tools, but hotels should combine both tools to achieve a better understanding of service quality. Both tools are useful and will be available in the future; what changes is that technology supports new ways of accessing these tools and reporting results. Finally, customers target online comments on problems that matter most to them and questionnaires are targeted by hoteliers in assessing problems and setting quality goals that matter most to them.

As already pointed out, future work in this research field should be implemented in other datasets of other regions. Additionally, the enhanced model dimensions could give interesting insights into the relation of the discussed dimensions with a reviewer's contributions. Moreover, the helpful votes a review gathers in relation to the dimensions it captures. Also, the reviewers' origin in relation to the dimensions discussed can bring interesting insights into visitors' preferences of different nationalities. It would also be interesting to expand the research to online reviews of other product and review providers (i.e., Amazon, Glassdoor, Facebook) in correlation to similar quality assessment tools. Finally, a compelling study would be to study the evolution of the dimensions in time by researching the monthly/seasonal/annual changes of dimensions in online reviews.

One of the study's contributions is the methodological approach to develop a model that brings together quality assessment surveys with online reviews discussed topics. This approach can be applied to other fields such as consumer product reviews and service/product assessment, develop other customizable models, and, consequently, more standardized data collection and, therefore, more easily administered and viewed analytics in those fields.

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## APPENDIX A. STRUCTURED INTERVIEW QUESTIONS

Name of the hotel(s) that you represent.

Your position at the hotel.

Are you interested in receiving the results? Yes No

In case you responded 'Yes' to the previous question, please provide us with your email.

Which ways do you use to assess the quality of the services that you offer?

-Questionnaires (Printed or Online)

-Online Reviews (i.e., Expedia, Booking.com, TripAdvisor) -Both

-Other (Please specify)……….

In case you use online reviews, please specify in ascending order of significance the platforms that you use (most important first).

Which hotel's needs do questionnaires cover and which do online reviews cover?

How easy is it to adapt and use each of the aforementioned tools (questionnaires, online reviews) as methods of quality assessment? Are there difficulties that have to be surpassed? Please, comment on your answer.

How reliable is the information provided by questionnaires in comparison to online reviews? Please, comment

Give us your insight on the quality of the information that each tool provides (questionnaires, online reviews)

What information is more difficult to find through questionnaires and what in online reviews. Please provide specific details (i.e. room cleanliness, restaurant service or pool evaluation and more)

Which of the aforementioned two tools (questionnaires, online reviews) provides you with more complete information? Why?

Have you taken any recent action based on the information you received from online reviews or questionnaires? Please, comment for each one separately

Do you think that there is a possibility that you will fully replace questionnaires with online reviews? Please, expand on your answer.

## APPENDIX B. TOP 1000 WORDS FREQUENCY

| N. Frequency - TopNouns | N. Frequency - TopNouns | N. Frequency - TopNouns | N. Frequency - TopNouns | N. Frequency - TopNouns |
|---|---|---|---|---|
| | 31. 7630 - center | 62. 4460 - sun | 93. 3030 - fruit | 124. 2107 - one |
| 1. 104100 - hotel | 32. 7556 - holiday | 63. 4429 - rest | 94. 3028 - thing | 125. 2085 - hospitality |
| 2. 46893 - room | 33. 7311 - price | 64. 4244 - front | 95. 3004 - team | 126. 2077 - manager |
| 3. 40778 - beach | 34. 7268 - crete | 65. 4094 - way | 96. 2984 - heraklion | 127. 2075 - toilet |
| 4. 30846 - staff | 35. 7110 - dinner | 66. 4068 - year | 97. 2949 - airport | 128. 2062 - cuisine |
| 5. 30635 - pool | 36. 7061 - village | 67. 4029 - chania | 98. 2899 - point | 129. 2036 - right |
| 6. 26764 - sea | 37. 6881 - terrace | 68. 3938 - money | 99. 2837 - wifi | 130. 2016 - kindness |
| 7. 22469 - breakfast | 38. 6875 - lot | 69. 3885 - garden | 100. 2752 - wine | 131. 1971 - board |
| 8. 21614 - food | 39. 6487 - city | 70. 3793 - home | 101. 2747 - thank | 132. 1967 - atmosphere |
| 9. 20862 - day | 40. 6463 - morning | 71. 3660 - animation | 102. 2640 - house | 133. 1966 - furniture |
| 10. 17591 - everything | 41. 6357 - floor | 72. 3655 - problem | 103. 2554 - value | 134. 1947 - entrance |
| 11. 15670 - view | 42. 6325 - quality | 73. 3555 - swimming | 104. 2497 - building | 135. 1944 - attention |
| 12. 13701 - location | 43. 6038 - nothing | 74. 3513 - structure | 105. 2490 - couple | 136. 1924 - change |
| 13. 13647 - place | 44. 6021 - bus | 75. 3492 - vacation | 106. 2479 - access | 137. 1922 - season |
| 14. 13475 - time | 45. 5849 - buffet | 76. 3415 - lunch | 107. 2445 - addition | 138. 1914 - taste |
| 15. 13224 - service | 46. 5623 - shower | 77. 3309 - part | 108. 2438 - bay | 139. 1900 - peace |
| 16. 12687 - restaurant | 47. 5459 - kitchen | 78. 3290 - cleanliness | 109. 2408 - juice | 140. 1889 - resort |
| 17. 11778 - area | 48. 5440 - cleaning | 79. 3212 - side | 110. 2407 - entertainment | 141. 1884 - meat |
| 18. 11379 - water | 49. 5390 - something | 80. 3209 - welcome | 111. 2369 - accommodation | 142. 1874 - clean |
| 19. 11123 - bar | 50. 5373 - owner | 81. 3188 - parking | 112. 2366 - number | 143. 1862 - stop |
| 20. 10589 - car | 51. 5372 - bed | 82. 3178 - walk | 113. 2318 - foot | 144. 1860 - club |
| 21. 10212 - bathroom | 52. 5263 - street | 83. 3166 - course | 114. 2318 - person | 145. 1850 - complex |
| 22. 9752 - stay | 53. 5253 - bit | 84. 3161 - arrival | 115. 2304 - music | 146. 1849 - tour |
| 23. 9596 - family | 54. 5184 - road | 85. 3158 - fridge | 116. 2282 - level | 147. 1834 - hour |
| 24. 9542 - night | 55. 5147 - town | 86. 3140 - tv | 117. 2244 - care | 148. 1809 - kitchenette |
| 25. 9037 - week | 56. 5109 - island | 87. 3132 - distance | 118. 2207 - space | 149. 1807 - selection |
| 26. 8948 - reception | 57. 4802 - conditioning | 88. 3121 - door | 119. 2177 - fact | 150. 1794 - greece |
| 27. 8734 - air | 58. 4779 - kind | 89. 3101 - noise | 120. 2173 - supermarket | 151. 1753 - bedroom |
| 28. 8214 - evening | 59. 4726 - everyone | 90. 3090 - trip | 121. 2158 - star | 152. 1742 - port |
| 29. 8039 - balcony | 60. 4650 - choice | 91. 3085 - end | 122. 2122 - anything | 153. 1729 - meal |
| 30. 7695 - apartment | 61. 4531 - coffee | 92. 3046 - table | 123. 2118 - sand | 154. 1714 - advice |

| N. Frequency - TopNouns | N. Frequency - TopNouns | N. Frequency - TopNouns | N. Frequency - TopNouns | N. Frequency - TopNouns |
|---|---|---|---|---|
| 620. 336 - corridor | 651. 312 - criticism | 682. 290 - relation | 713. 275 - france | 744. 257 - behaviour |
| 621. 336 - body | 652. 311 - mr. | 683. 290 - passage | 714. 274 - website | 745. 256 - chersonissos |
| 622. 334 - basement | 653. 309 - ridge | 684. 289 - desire | 715. 273 - partner | 746. 256 - slope |
| 623. 333 - architecture | 654. 309 - canteen | 685. 289 - clientele | 716. 272 - chocolate | 747. 255 - waterfront |
| 624. 332 - welcoming | 655. 308 - greeks | 686. 289 - church | 717. 272 - vehicle | 748. 255 - etc. |
| 625. 331 - cash | 656. 308 - state | 687. 288 - crowds | 718. 271 - cold | 749. 254 - plan |

| | | | | |
|---|---|---|---|---|
| 626. 331 - knossos | 657. 307 - recommend | 688. 288 - basket | 719. 270 - fortress | 750. 254 - eye |
| 627. 330 - lawn | 658. 306 - toast | 689. 287 - hygiene | 720. 270 - bacon | 751. 253 - treat |
| 628. 329 - luck | 659. 305 - spinalonga | 690. 286 - let | 721. 270 - ps | 752. 252 - guy |
| 629. 326 - share | 660. 304 - girlfriend | 691. 286 - disadvantage | 722. 269 - pelagia | 753. 252 - cereal |
| 630. 325 - seaside | 661. 302 - starting | 692. 286 - swim | 723. 268 - winter | 754. 252 - tui |
| 631. 325 - highlight | 662. 301 - ac | 693. 285 - bravo | 724. 268 - director | 755. 252 - joy |
| 632. 324 - shore | 663. 301 - height | 694. 285 - dog | 725. 267 - run | 756. 251 - difficulty |
| 633. 324 - tray | 664. 300 - parasol | 695. 285 - grocery | 726. 266 - ceiling | 757. 251 - bathing |
| 634. 324 - sunday | 665. 300 - mare | 696. 285 - royal | 727. 266 - boyfriend | 758. 251 - speaking |
| 635. 324 - dance | 666. 299 - sign | 697. 283 - golf | 728. 266 - scooter | 759. 251 - elafonisi |
| 636. 323 - trouble | 667. 299 - deposit | 698. 282 - drinking | 729. 266 - rice | 760. 251 - nikolaos |
| 637. 322 - fitness | 668. 297 - face | 699. 281 - fault | 730. 265 - pork | 761. 250 - april |
| 638. 321 - mrs. | 669. 296 - notch | 700. 281 - cool | 731. 265 - c | 762. 250 - pan |
| 639. 321 - contact | 670. 296 - neat | 701. 277 - highway | 732. 265 - lounger | 763. 250 - concept |
| 640. 320 - employee | 671. 296 - blue | 702. 277 - picture | 733. 265 - salt | 764. 249 - yoghurt |
| 641. 320 - falasarna | 672. 295 - anna | 703. 277 - today | 734. 264 - clay | 765. 249 - mass |
| 642. 319 - clock | 673. 294 - treatment | 704. 277 - agia | 735. 264 - samaria | 766. 249 - plumbing |
| 643. 319 - warmth | 674. 293 - minimum | 705. 276 - katerina | 736. 263 - communication | 767. 248 - animator |
| 644. 319 - plant | 675. 293 - oasis | 706. 276 - doubt | 737. 263 - shuttle | 768. 246 - suitcase |
| 645. 318 - staircase | 676. 292 - museum | 707. 276 - lake | 738. 262 - smiling | 769. 245 - ouzo |
| 646. 317 - bakery | 677. 292 - disposal | 708. 276 - map | 739. 261 - complaint | 770. 245 - villas |
| 647. 316 - gift | 678. 291 - mold | 709. 275 - opposite | 740. 259 - sissi | 771. 245 - dark |
| 648. 316 - scale | 679. 291 - inconvenience | 710. 275 - manolis | 741. 259 - feta | 772. 244 - color |
| 649. 316 - noisy | 680. 291 - iron | 711. 275 - dust | 742. 259 - alley | 773. 244 - sunbed |
| 650. 314 - stella | 681. 290 - theme | 712. 275 - section | 743. 258 - fi | 774. 243 - approach |

| **N. Frequency - TopNouns** | **N. Frequency - TopNouns** | **N. Frequency - TopNouns** | **N. Frequency - TopNouns** | **N. Frequency - TopNouns** |
|---|---|---|---|---|
| 775. 243 - pay | 806. 231 - tree | 837. 217 - weekend | 868. 207 - sauna | 899. 196 - grove |
| 776. 242 - gel | 807. 231 - turkey | 838. 217 - depth | 869. 207 - lidl | 900. 196 - hostel |
| 777. 241 - signal | 808. 230 - sight | 839. 217 - wood | 870. 207 - sunrise | 901. 196 - driver |
| 778. 241 - step | 809. 230 - rack | 840. 217 - background | 871. 206 - negative | 902. 196 - compliment |
| 779. 240 - none | 810. 229 - meeting | 841. 217 - descent | 872. 205 - picturesque | 903. 196 - opening |
| 780. 240 - = | 811. 227 - improvement | 842. 216 - satisfaction | 873. 205 - breeze | 904. 196 - soup |
| 781. 240 - spring | 812. 227 - grill | 843. 216 - support | 874. 204 - panorama | 905. 195 - discos |
| 782. 239 - cup | 813. 227 - relax | 844. 216 - exception | 875. 203 - limit | 906. 195 - delight |
| 783. 239 - youth | 814. 227 - melon | 845. 216 - eur | 876. 203 - simplicity | 907. 194 - minibar |
| 784. 239 - sauce | 815. 226 - sheet | 846. 215 - ease | 877. 203 - birthday | 908. 194 - quad |
| 785. 239 - success | 816. 226 - electricity | 847. 213 - chaos | 878. 202 - ask | 909. 194 - creta |
| 786. 237 - cottage | 817. 226 - deckchair | 848. 213 - microwave | 879. 202 - credit | 910. 193 - master |
| 787. 237 - check-in | 818. 225 - â€œ | 849. 213 - housing | 880. 202 - marmara | 911. 193 - savory |
| 788. 236 - turn | 819. 225 - absence | 850. 212 - wi | 881. 202 - schedule | 912. 193 - bike |
| 789. 236 - sympathy | 820. 225 - europe | 851. 212 - discovery | 882. 201 - school | 913. 193 - well-being |
| 790. 236 - gentleman | 821. 223 - tub | 852. 212 - beware | 883. 201 - stairs | 914. 193 - gem |
| 791. 235 - scenery | 822. 223 - neighbor | 853. 212 - embankment | 884. 201 - jet | 915. 192 - story |
| 792. 235 - break | 823. 223 - toaster | 854. 211 - route | 885. 201 - medium | 916. 192 - bedside |
| 793. 234 - vegetation | 824. 223 - mistake | 855. 211 - activity | 886. 200 - comment | 917. 191 - sandwich |

| | | | | |
|---|---|---|---|---|
| 794. 234 - control | 825. 222 - lamb | 856. 211 - sky | 887. 199 - humor | 918. 191 - walking |
| 795. 234 - train | 826. 222 - safe | 857. 210 - disaster | 888. 199 - sewage | 919. 191 - track |
| 796. 234 - honeymoon | 827. 221 - speed | 858. 210 - eva | 889. 199 - laundry | 920. 191 - culture |
| 797. 233 - lift | 828. 221 - worthy | 859. 210 - court | 890. 199 - tomato | 921. 190 - list |
| 798. 233 - quantity | 829. 221 - taverna | 860. 209 - paleochora | 891. 198 - future | 922. 190 - eleni |
| 799. 233 - answer | 830. 221 - settlement | 861. 209 - field | 892. 197 - upgrade | 923. 189 - waitress |
| 800. 233 - outdoor | 831. 220 - football | 862. 209 - lagoon | 893. 197 - ierapetra | 924. 189 - truth |
| 801. 233 - maximum | 832. 220 - insurance | 863. 209 - history | 894. 197 - household | 925. 189 - volleyball |
| 802. 232 - cm | 833. 219 - advise | 864. 209 - channel | 895. 197 - soundproofing | 926. 188 - quieter |
| 803. 232 - santorini | 834. 219 - ventilation | 865. 209 - seat | 896. 197 - crowd | 927. 188 - stuff |
| 804. 232 - television | 835. 218 - loutro | 866. 208 - repair | 897. 197 - cactus | 928. 186 - slide |
| 805. 231 - drain | 836. 217 - bag | 867. 208 - dimitris | 898. 196 - trash | 929. 185 - knowledge |

| **N. Frequency - TopNouns** | **N. Frequency - TopNouns** | **N. Frequency - TopNouns** |
|---|---|---|
| 930. 185 - joke | 961. 178 - wish | 992. 168 - flag |
| 931. 185 - layout | 962. 177 - north | 993. 167 - tap |
| 932. 185 - majority | 963. 177 - comparison | 994. 167 - sugar |
| 933. 184 - screen | 964. 177 - basis | 995. 166 - hope |
| 934. 184 - land | 965. 177 - pharmacy | 996. 166 - bonus |
| 935. 184 - hillside | 966. 177 - bbq | 997. 166 - dimitri |
| 936. 184 - approx | 967. 176 - present | 998. 166 - cicadas |
| 937. 184 - cove | 968. 176 - rain | 999. 166 - champagne |
| 938. 183 - while | 969. 176 - bill | 1000. 165 - judgment |
| 939. 182 - touch | 970. 175 - damage | 1001. 165 - espresso |
| 940. 182 - stress | 971. 175 - date | 1002. 165 - polite |
| 941. 182 - network | 972. 175 - germany | |
| 942. 182 - breathtaking | 973. 175 - wait | |
| 943. 182 - fireplace | 974. 175 - capital | |
| 944. 182 - appearance | 975. 175 - yesterday | |
| 945. 181 - therefore | 976. 174 - hire | |
| 946. 181 - tripadvisor | 977. 174 - email | |
| 947. 181 - italy | 978. 173 - boy | |
| 948. 180 - ferry | 979. 173 - round | |
| 949. 180 - rock | 980. 173 - helpfulness | |
| 950. 180 - lighting | 981. 172 - tomorrow | |
| 951. 179 - supply | 982. 171 - fine | |
| 952. 179 - sofia | 983. 171 - administrator | |
| 953. 179 - energy | 984. 170 - combination | |
| 954. 179 - play | 985. 170 - convenience | |
| 955. 179 - well | 986. 170 - character | |
| 956. 179 - operation | 987. 169 - wonderful | |
| 957. 178 - fishing | 988. 169 - bowl | |
| 958. 178 - souvenir | 989. 169 - charming | |
| 959. 178 - stalida | 990. 169 - sitia | |
| 960. 178 - correct | 991. 169 - inside | |

## APPENDIX C. ENHANCED CATEGORIZATION WITH SENTIMENT

| TABLE 1 ENHANCED CATEGORIZATION WITH SENTIMENT | | | |
|---|---|---|---|
| | Sentiment | Frequency | |
| TANGIBLES | 1 | 129,640 | 79% |
| | 0 | 34,349 | 21% |
| INTANGIBLES | 1 | 401,558 | 77% |
| | 0 | 118,737 | 23% |
| TOTAL | 1 | 531,198 | 78% |
| | 0 | 153,086 | 22% |

| TABLE 2 ENHANCED CATEGORIZATION WITH SENTIMENT | | | |
|---|---|---|---|
| | Sentiment | Frequency | Percentage |
| TANGIBLES | 1 | 350010 | 78% |
| | 0 | 100373 | 22% |
| VALUE | 1 | 51548 | 74% |
| | 0 | 18364 | 26% |
| RELIABILITY | 1 | 28678 | 79% |
| | 0 | 7624 | 21% |
| RESPONSIVENESS | 1 | 13048 | 77% |
| | 0 | 3994 | 23% |
| ASSURANCE | 1 | 45048 | 79% |
| | 0 | 11693 | 21% |
| EMPATHY | 1 | 42866 | 80% |
| | 0 | 11038 | 20% |
| TOTAL | 1 | 531,198 | 78% |
| | 0 | 153,086 | 22% |

| TABLE 3 ENHANCED CATEGORIZATION WITH SENTIMENT | | | |
|---|---|---|---|
| | Sentiment | Frequency | Percentage |
| ROOM | 1 | 45,960 | 75% |
| | 0 | 15,079 | 25% |
| ROOM_AMENITIES | 1 | 30,207 | 74% |
| | 0 | 10,838 | 26% |
| BATHROOM | 1 | 13,777 | 63% |

| | | | |
|---|---|---|---|
| | 0 | 8,202 | 37% |
| HOTEL | 1 | 91,719 | 77% |
| | 0 | 27,643 | 23% |
| SURROUNDINGS | 1 | 123,519 | 82% |
| | 0 | 27,281 | 18% |
| FACILITIES | 1 | 48,526 | 78% |
| | 0 | 13,979 | 22% |
| FOOD_DRINKS | 1 | 43,402 | 76% |
| | 0 | 13,821 | 24% |
| EMPLOYEES#CUSTOMER_CARE | 1 | 83,075 | 79% |
| | 0 | 21,549 | 21% |
| EMPLOYEES#SERVICE | 1 | 4,448 | 70% |
| | 0 | 1,894 | 30% |
| SOUNDNESS | 1 | 46,565 | 78% |
| | 0 | 12,800 | 22% |
| **TOTAL** | 1 | 531,198 | 78% |
| | 0 | 153,086 | 22% |

TABLE 4 ENHANCED CATEGORIZATION WITH SENTIMENT

| RELATION | RELATION | | P/N | FREQUENCY | PERCENTAGE |
|---|---|---|---|---|---|
| TANGIBLES | SERVQUAL, HOLSERV | ROOM#DESIGN_FEATURES | 1 | 3,766 | 72% |
| | | | 0 | 1,460 | 28% |
| TANGIBLES | HOLSERV+ | ROOM#CLEANLINESS | 1 | 13,338 | 77% |
| | | | 0 | 4,071 | 23% |
| TANGIBLES | HOLSERV+ | ROOM#COMFORT | 1 | 12,689 | 74% |
| | | | 0 | 4,497 | 26% |
| TANGIBLES | HOLSERV+ | ROOM_AMENITIES#USER_FRIENDLY | 1 | 583 | 69% |
| | | | 0 | 256 | 31% |
| TANGIBLES | HOLSERV+ | ROOM_AMENITIES#EQUIPMENT | 1 | 22,556 | 76% |
| | | | 0 | 7,108 | 24% |
| VALUE | DESCRIPTIVE ANALYSIS | ROOM_AMENITIES#PRICES | 1 | 753 | 65% |
| | | | 0 | 408 | 35% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM_AMENITIES#QUALITY | 1 | 2,345 | 74% |
| | | | 0 | 843 | 26% |
| VALUE | DESCRIPTIVE ANALYSIS | ROOM#OVERALL_VALUE | 1 | 3,468 | 77% |
| | | | 0 | 1,044 | 23% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#PRICES | 1 | 194 | 69% |
| | | | 0 | 87 | 31% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#INTERNET | 1 | 920 | 67% |
| | | | 0 | 446 | 33% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM_AMENITIES#BED_COMFORT | 1 | 3,970 | 64% |
| | | | 0 | 2,223 | 36% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#SIZE | 1 | 3,708 | 78% |
| | | | 0 | 1,042 | 22% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | ROOM#FURNITURE | 1 | 7,877 | 76% |
| | | | 0 | 2,432 | 24% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | BATHROOM#CLEANLINESS | 1 | 5,248 | 61% |
| | | | 0 | 3,366 | 39% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | BATHROOM#EQUIPMENT | 1 | 1,608 | 54% |
| | | | 0 | 1,389 | 46% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | BATHROOM#SIZE | 1 | 6,921 | 67% |
| | | | 0 | 3,447 | 33% |
| RELATION | RELATION | HOTEL | | | |

| | | | | | |
|---|---|---|---|---|---|
| TANGIBLES | SERVQUAL, HOLSERV | HOTEL#DESIGN_FEATURES | 1 | 6,326 | 78% |
| | | | 0 | 1,789 | 22% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#GUEST_CUSTOMIZED | 1 | 12,281 | 82% |
| | | | 0 | 2,722 | 18% |
| VALUE | DESCRIPTIVE ANALYSIS | HOTEL#PRICES | 1 | 5,073 | 70% |
| | | | 0 | 2,183 | 30% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#QUALITY | 1 | 14,305 | 72% |
| | | | 0 | 5,516 | 28% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#COMFORT | 1 | 9,184 | 82% |
| | | | 0 | 2,017 | 18% |
| VALUE | DESCRIPTIVE ANALYSIS | HOTEL#OVERALL_VALUE | 1 | 29,416 | 75% |
| | | | 0 | 9,929 | 25% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#CLEANLINESS | 1 | 4,617 | 70% |
| | | | 0 | 2,011 | 30% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | HOTEL#AMBIANCE | 1 | 10,517 | 88% |
| | | | 0 | 1,476 | 12% |
| **RELATION** | **RELATION** | **FACILITIES** | | | |
| TANGIBLES | SERVQUAL, HOLSERV | FACILITIES#DESIGN_FEATURES | 1 | 18,339 | 80% |
| | | | 0 | 4,547 | 20% |
| VALUE | DESCRIPTIVE ANALYSIS | FACILITIES#PRICES | 1 | 4,718 | 81% |
| | | | 0 | 1,137 | 19% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FACILITIES#QUALITY | 1 | 11,530 | 81% |
| | | | 0 | 2,678 | 19% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FACILITIES#COMFORT | 1 | 9,361 | 72% |
| | | | 0 | 3,611 | 28% |
| TANGIBLES | DESCRIPTIVE ANALYSIS | FACILITIES#CLEANLINESS | 1 | 4,578 | 70% |
| | | | 0 | 2,006 | 30% |
| **RELATION** | **RELATION** | **FOOD_DRINKS** | | | |
| TANGIBLES | HOLSERV+ | FOOD_DRINKS#STYLE_OPTIONS | 1 | 13,622 | 79% |
| | | | 0 | 3,548 | 21% |
| TANGIBLES | HOLSERV+ | FOOD_DRINKS#QUALITY | 1 | 8,654 | 74% |
| | | | 0 | 3,056 | 26% |
| VALUE | DESCRIPTIVE ANALYSIS | FOOD_DRINKS#PRICES | 1 | 7,995 | 69% |
| | | | 0 | 3,651 | 31% |

| | | | | | |
|---|---|---|---|---|---|
| TANGIBLES | DESCRIPTIVE ANALYSIS | FOOD_DRINKS#OVERALL_VALUE | 1 | 13,131 | 79% |
| | | | 0 | 3,566 | 21% |
| **RELATION** | **RELATION** | **SURROUNDINGS** | | | |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#LOCATION | 1 | 50,972 | 82% |
| | | | 0 | 11,345 | 18% |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#NEARBY_AMENITIES | 1 | 28,648 | 82% |
| | | | 0 | 6,283 | 18% |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#TRANSPORT | 1 | 6,284 | 79% |
| | | | 0 | 1,688 | 21% |
| TANGIBLES | HOLSERV+ | SURROUNDINGS#ATTRACTIONS | 1 | 37,615 | 83% |
| | | | 0 | 7,965 | 17% |
| **RELATION** | **RELATION** | **SERVICE / EMPLOYEES** | | | |
| TANGIBLES | SERVQUAL, HOLSERV | SERVICE#APPEARANCE | 1 | 1,029 | 73% |
| | | | 0 | 388 | 27% |
| TANGIBLES | SERVQUAL, HOLSERV | SERVICE#CLEANLINESS | 1 | 2,735 | 70% |
| | | | 0 | 1,173 | 30% |
| VALUE | DESCRIPTIVE ANALYSIS | SERVICE#PRICE | 1 | 684 | 67% |
| | | | 0 | 333 | 33% |
| **RELATION** | **RELATION** | **CUSTOMER CARE / EMPLOYEES** | | | |
| RESPONSIVENES S | SERVQUAL, HOLSERV | CUSTOMER_CARE#SCHEDULE_ACCURACY | 1 | 770 | 69% |
| | | | 0 | 343 | 31% |
| RESPONSIVENES S | SERVQUAL, HOLSERV | CUSTOMER_CARE#PROMPTNESS | 1 | 7,143 | 76% |
| | | | 0 | 2,224 | 24% |
| RESPONSIVENES S | SERVQUAL, HOLSERV | CUSTOMER_CARE#EAGERNESS | 1 | 5,135 | 78% |
| | | | 0 | 1,427 | 22% |
| ASSURANCE | SERVQUAL, HOLSERV | CUSTOMER_CARE#COURTEOUS | 1 | 21,732 | 82% |
| | | | 0 | 4,874 | 18% |
| ASSURANCE | SERVQUAL, HOLSERV | CUSTOMER_CARE#KNOWLEDGABLE_and_SKILLFU L | 1 | 8,154 | 75% |
| | | | 0 | 2,686 | 25% |
| EMPATHY | SERVQUAL, HOLSERV | CUSTOMER_CARE#CUSTOMER_CENTERED | 1 | 27,131 | 82% |
| | | | 0 | 5,941 | 18% |
| EMPATHY | SERVQUAL, HOLSERV | CUSTOMER_CARE#UNDERSTANDING_SPECIAL_NE EDS | 1 | 13,010 | 76% |
| | | | 0 | 4,054 | 24% |
| **RELATION** | **RELATION** | **SOUNDNESS** | | | |

| | | | | | |
|---|---|---|---|---|---|
| EMPATHY | SERVQUAL, HOLSERV | SOUNDNESS#CONVENIENT_OPERATING_HOURS | 1 | 2,725 | 72% |
| | | | 0 | 1,043 | 28% |
| RELIABILITY | SERVQUAL, HOLSERV | SOUNDNESS#SERVICE_ON_TIME_WHEN_PROMISED | 1 | 2,365 | 76% |
| | | | 0 | 755 | 24% |
| RELIABILITY | SERVQUAL, HOLSERV | SOUNDNESS#EFFICIENCY | 1 | 1,055 | 75% |
| | | | 0 | 350 | 25% |
| RELIABILITY | SERVQUAL, HOLSERV | SOUNDNESS#PROBLEM_ADMINISTRATION | 1 | 4,239 | 63% |
| | | | 0 | 2,452 | 37% |
| RELIABILITY | SERVQUAL, HOLSERV | SOUNDNESS#RECOMMENDABLE | 1 | 20,109 | 84% |
| | | | 0 | 3,709 | 16% |
| RELIABILITY | DESCRIPTIVE ANALYSIS | SOUNDNESS#MANAGEMENT | 1 | 910 | 72% |
| | | | 0 | 358 | 28% |
| ASSURANCE | SERVQUAL, HOLSERV | SOUNDNESS#WITHOUT_MISTAKES | 1 | 2,237 | 61% |
| | | | 0 | 1,440 | 39% |
| ASSURANCE | SERVQUAL, HOLSERV | SOUNDNESS#INSTILLING_CONFIDENCE | 1 | 8,322 | 88% |
| | | | 0 | 1,115 | 12% |
| ASSURANCE | SERVQUAL, HOLSERV | SOUNDNESS#SECURITY | 1 | 4,603 | 74% |
| | | | 0 | 1,578 | 26% |
| | | **TOTAL** | 1 | 531,199 | 78% |
| | | | 0 | 153,086 | 22% |