Mediterranean Journal of Social & Behavioral Research
2023, 7(1), 29-41
ISSN 2547-8559 (Print)
ISSN 2547-8567 (Online)
https://www.mjosbr.com/

Research Article OPEN ACCESS

SentiSfaction: New cultural way to measure tourist COVID-19 mobility in Italy

Concetta Papapicco [1]*

[1] University of Bari "Aldo Moro", Bari, ITALY
***Corresponding Author:** concy81192@hotmail.it

Citation: Papapicco, C. (2023). SentiSfaction: New cultural way to measure tourist COVID-19 mobility in Italy. *Mediterranean Journal of Social & Behavioral Research*, 7(1), 29-41. https://doi.org/10.30935/mjosbr/12790

ABSTRACT

From a psycho-linguistic and marketing perspective, the research fits into the evaluation of in the context of tourism and, in particular, tourism mobility, targeting one of the leading Italian rail transport companies, namely Trenitalia. This study, conducted on tweets, aims to examine how talks about the transport service offered by Trenitalia. A total of 674 tweets for the tourist season 2019 and 100 tweets for the tourist season 2020 were collected following the pre-COVID-19 and COVID-19 period. The methodology is the application of sentiment analysis (SA) that produces quantitative and qualitative results. For the quantitative part, the sentiment was calculated first automatically via the Sentistrength software, then an extraction of the frequencies and calculation of the dependence (Chi-square statistic and t-test) between year and polarity was conducted with R, statistical software. The results show that SA is a good methodology of analysis of the online reputation and customer satisfaction of a company that deals with tourism, also in the difference between pre-COVID-19 and COVID-19 period.

Keywords: e-tourism mobility, Twitter, sentiment analysis, customer satisfaction, COVID-19 period

Received: 05 Sep. 2022 ◆ Accepted: 27 Dec. 2022

INTRODUCTION

Customer satisfaction (CS) in the tourism sector, although it is a very studied construction (Sánchez-Rebull et al., 2018), becomes difficult to detect because of its multidimensionality (Rathnayake, 2015). In addition, in tourism, the definition is complex and has a multi-dimensional nature (Smith, 1998) because must consider the feelings of gratification or displeasure, if the tourist is satisfied or dissatisfied (Chen & Chen, 2010). As a result, the CS analysis must return a key to judgment a tourism service (Rathnayake, 2015), playing a critical role in the success of firms and products (Campo & Yagüe, 2009; Campo-Martínez & Garau-Vadell, 2010; Chang, 2008; Lee et al., 2010; Nowak & Sahli, 2007). In this complexity, this research focuses on a dimension of CS in tourist mobility, or the link between experience and emotional involvement mediated by social networks. In addition, according to the literature on CS in tourism, it emerges that CS has been analysed in different subsectors of tourism, for example:

(1) agro-tourism (Chatzigeorgiou et al., 2009),
(2) rural tourism (Leingpibul et al., 2009; Loureiro, 2010),
(3) sport tourism (Martin & O'Neill, 2010),
(4) alternative tourism (Deaden & Harron, 1994),
(5) cruise tourism (Hwang & Han, 2014; Zhang et al., 2015),
(6) air transport (Ginieis et al., 2012), and
(7) hospitality enterprises (Barsky, 1992; Choi & Chu, 2001; Deng et al., 2013; Fah & Kandasamy, 2011; Motlagh et al., 2013; Zhou et al., 2014).

Zhou et al. (2014) find that 21 of the 24 published studies on CS and 11 of 12 on service quality deal with hotel and restaurant tourist sectors. They, therefore, conclude that more research on CS and service quality is needed in other tourist contexts (Sánchez-Rebull et al., 2018, p. 3). Starting from this research gap, the research aims at showing a methodology that can be applied to measure the emotional dimension of satisfaction in tourist mobility in rail transport. The focus on the emotions of consumers is also linked to the period of pandemic when tourism mobility changes. In particular, COVID-19 outbreaks has also blocked tourism and, as a result, mobility, changing practices and organization. Researchers have started to focus on this area, but the work available so far is limited (Sharma et al., 2021). Starting from this and the previous research gaps, the study aims to answer the following research questions:

1. **RQ1:** How much the review of a tourist mobility service can be affected by the period in which you travel?
2. **RQ2:** Starting from the results of **RQ1**, we wondered if a mixed methodology of analysis of CS, i.e., sentiment analysis (SA), can be an optimal strategy to capture all the multidimensionality of the construct of CS.

On the basis of these research questions, the following consequential hypotheses have been formulated:

1. **H1:** There is a dependence between the calculated sentiment indicating the satisfaction of Trenitalia's customer and the travel period (pre-COVID-19 period vs. COVID-19 period).
2. **H2:** In case of dependence, this is not due to the case.
3. **H3:** In case of non-random dependence, the mixed methodology can be a useful strategy to consider the multidimensionality of CS in tourist mobility.

Indeed, in the field of computational psycho-linguistics, the research proposes the study of an Italian case, namely Trenitalia, a leading company in rail transport. This study, conducted on tweets posted by Twitter users, aims to examine how talks about the transport service offered by Trenitalia. Another objective that the research aims to achieve is to prove that, based on the sentiment obtained (positive, negative, or neutral) companies can collect important information about the points of strength and weakness of service or product. In the study, the tweets of users during the summer holidays of 2019 and 2020 were collected. The total is 674 tweets for the tourist season 2019 and 100 tweets for the tourist season 2020.

In general, the results show that SA is a good methodology of analysis of the online reputation and CS of a company that deals with tourism. One should, however, think of mixed methodologies (quanti-qualitative or quali-quantitative) so that the result is understood by the company to identify the strengths and intervene on the weak points of the service.

TOURIST CUSTOMER SATISFACTION IN ETOURISM MOBILITY: RELATED WORKS

The psychology of tourism is a science that uses theories and knowledge of psychological processes to take care of "man as a tourist" (Mereu, 2004, 2010). With the transition from elitist tourism to etourism, there is an increase in research aimed at verifying the use of social networks to organize travel or research aimed at investigating the CS of companies dealing with tourism. With the spread of new media, which uses digital language (Gui, 2014, p. 25), the experience of travellers is transformed. Of course, also tourism was invested by the "great maelstrom" (De Kerckhove, 2003) of the Internet. Today, in the discursive construction made by social networks, the tourist experience is a "life form" (Manuti et al., 2007, p. 1) linking the use of mobility technologies (aircraft, cars, ships, and trains) to stay in certain places, in a final assessment expressing satisfaction, or dissatisfaction of people. The human experience is largely mediated, that is, characterized by artefacts that manage in an increasingly complex way the practices of attribution of meaning. For this reason, the psychological issues related to the various areas of human-mediated experience can be addressed with greater productivity with qualitative-quantitative approaches. The instrument that is more congenial to the union of the two methodologies is SA, which, starting from textual sources, returns quantitative data. Knowing "what other people think" (Pang & Lee, 2008, p. 1) has always been an important element of information that characterizes the decision-making processes, such as that of organizing a trip, which is the result of a series of decisions that the tourist must make. The decision-making process in tourism is quite complex, as it is necessary first of all that the person is driven and motivated to travel, then that he can choose a destination based on the motivation and, from these two aspects, the result is others such as the choice of accommodation or the type of transport useful to reach the chosen location. van Raaij and Francken (1984) designed a model consisting of four steps that characterize the moments of decision-making in the organization of a trip:

1. **General decision:** It is the starting point of the decision-making process, and it is at this stage that the traveller decides to leave,
2. **Acquisition of information on possible destinations and itineraries:** It is precisely at this stage that tourism marketing and web marketing strategies have been developed,
3. **Joint decision:** In the case of family or group trips, and
4. **Activities in a specific sense:** This is the last step and concerns the real tourist experience.

The decision-making process and other variables such as motivation, communication levers, self-image are aspects that form the point of contact between tourism and psychology, giving rise to the branch of tourism psychology.

The psychology of tourism is a science that uses theories and knowledge of the psychological and marketing field. With the transition from elitist tourism to etourism, there is an increase in research aimed at verifying the use of social networks to organize travel or research aimed at investigating the CS of companies dealing with tourism. With the spread of new media, which use digital language (Gui, 2014, p. 25), the situations experienced by travellers is transformed: the virtual communities in which it is possible to exchange travel information, feedback systems shall be developed to assess facilities hotels; online tour operators are born and are gradually replacing travel agencies; the development of digital museums guide or technological souvenirs; are growing also systems for evaluating the services offered by companies dealing with mobility (for example Trenitalia for rail transport) or by entities interested in enhancing tourist destinations. Since tourism is a mass phenomenon in our time, it involves the lives of many people and organizes the organization of entire communities. A concise definition but at the same time such as to render it complex describes tourism as:

> "the sum of the relationships arising the interaction of tourists, business suppliers, host governments and host communities in the process of attracting tourist and other visitors" (Mcintosh & Goeldner, 1984, p. 3).

Of course, tourism was also invested by the "great maelstrom" of the Internet (De Kerckhove, 2003). Today, in the discursive construction carried out by social networks, the tourist experience is a "life form" (Manuti et al., 2007, p. 1) that connects the use of mobility technologies (aircraft, cars, ships, trains) to stay in certain places, in a final assessment that expresses the satisfaction or dissatisfaction of people.

This research investigates the practices of sense-making that are organized at the interface between two important areas in contemporary human experience: the media and travel, above all in two important historical periods, i.e., the pre-COVID-19 mobility and the COVID-19 mobility. Following the spread of social networks, there is an increasing tendency on the part of companies to want to keep under control, in addition to their online presence, even the management of their product or service: it is talked about, therefore, of online reputation and CS. In this regard, however, it is necessary to reflect on what is meant by reputation and CS. “Reputation is that set of beliefs, assessments and perceptions that a community formulates about the individual” (Cavazza, 2012, p. 27). The reputation, however, only makes sense when the system of values and perceptions that constitute it is shared by a social group, inserted not necessarily in a physical space, but also symbolic, like the virtual one. In addition to the collective dimension, there is an individual dimension to reputation: every person can act actively on his or her reputation. Companies and organizations also have a reputation. Companies, like Trenitalia, aim to control their reputation, which is the result of the articulation between being known for something in a certain way. The company’s reputation is the result of a communicative action arising from the interaction between the organization and its stakeholders. In the tourist industry, many hotels tend to calculate their reputation based on feedback systems left by users. Receiving much positive feedback is a symptom of popularity. The creation of a web reputation monitoring system of a company or brand is based on several concrete applications: an empirical analysis of customer feedbacks and dialogue with customers. In particular, the monitoring informs about problems encountered by the customer concerning the services/products provided by the company and may result in the need to improve some aspects related to its activities, such as the service of front office customers and product/service quality: this is the CS. However, CS in the field of tourist mobility is a multidimensional construct and, for this reason, very difficult to define and detect. Thus, CS in tourist mobility is determined by both subjective (i.e., customer needs and emotions) and objective factors (i.e., product and service features), however, as in the definition of CS, a complete set of attributes that determines CS in tourism does not exist in the literature (Sánchez-Rebull et al., 2018). In this study, the link between consumer experience and emotionality will be considered as a dimension of CS. In this regard, Gountas and Gountas (2007) explain how emotional reactions to service context influences CS. Chatzigeorgiou et al. (2009) conclude that customer emotions are a key determinant to CS and repeated visits. In other words, satisfaction is defined as a tourist’s affective state, resulting from an overall appraisal of psychological preference and pleasure towards the tourist destination (Huang et al., 2006). In addition, the analysis of CS becomes even more complex during the period COVID-19 in which the circulation of the new coronavirus has led to the difficulty of mobility (Iaquinto, 2020), especially in the tourism sector. This has had an impact on tourist companies and especially on tourist transport companies, such as those on rails, the subject of research. The current research on the link between tourist companies and COVID-19 focus mainly on the current and perceived socio-economic contributions of tourism to the target communities (Lindberg & Johnson, 1997). In particular, these studies focus on the socio-economic impacts of tourism in times of crisis (Lindberg et al., 2001; Torre & Scarborough, 2017) such as the health crisis from COVID-19.

Moreover, in this delicate historical period, the digitization of tourism also leads to increased control by companies of online presence and its online reputation. The web presence is the space that a company employs on the web, investing in branding, promotion and online marketing. In this landscape, the web reputation, that is the result of communicative action, deriving from the interaction between the organization and its stakeholders (Cavazza, 2012, p. 93). In semiotics, the web reputation and web presence can be understood as an effect of meaning that emerges from multiple practices of recognition-management-bargaining content through which a subject of the statement marks its presence within a conversation on social media (Peverini, 2014, p. 230). In this way, the object and procedure of investigation are particularly congruent because are framed in the same horizon of meaning: cyberspace. Indeed, cyberspace becomes a place, and at the same time, a means used by customers to express their satisfaction with the service or product. From a business point of view, CS is seen as a key indicator to understand the strengths and weaknesses of the service offered (Dash et al., 2021). Satisfying customers is critical, and more research has been done in this area. This area of investigation, mainly covered by marketing, includes the strategic side of the organization, CS, service quality, company associations, relative costs, increased competition, new product activities, employee capabilities, and efficiency (Hult et al., 2019). These connections have also been recognized in the academic literature (Gummesson, 1998; Hoyer & MacInnis, 2001; Molinari et al., 2008; Ardani et al., 2019). However, the study on CS from the tourist perspective research is sparse; more research is needed on CS from the tourist perspective (Ravishankar & Christopher, 2020). CS can be related to feelings of enjoyment, acceptance, ease, and happiness (Sari et al., 2019). Starting from the feelings of the customers, as a basis of CS in the field of tourism, this work will focus on a methodology useful to detect the emotions of tourists, namely SA.

This important tool for calculating online reputation originates from natural language processing (NLP). Besides, SA is based on computational linguistics techniques and text mining of which it can be said that it is a specialization. As regards the methodological aspect, the software currently on the market is based on techniques such as syntactic and semantic analysis of the text, the interpretation of written language, the identification of idioms, statistical analysis and the repetition of keywords. Most of these software makes use of classification algorithms both to collect and discriminate documents and to detect positive/negative polarities within the text, distinguishing different levels of sentiment intensity. SA is part of the disciplinary field of sentic computing (SC), a transversal field of research.

INSIDE SENTIC COMPUTING: SENTIMENT ANALYSIS AS A WAY TO MEASURE CUSTOMER SATISFACTION

SC is a disciplinary field introduced by Cambria and Hussain (2012) whose study focuses on how computers can detect human emotionality, starting, for example, from textual data. The term ‘sentic’ (Cambria & Hussain, 2012, 1) itself describes the approach of this multidisciplinary field. Sentic is the contraction of ‘sentiment’ in which are enclosed all studies of affective computing and ‘common sense’, linked to the opinions of human beings that can be investigated.

Because it combines different disciplines, it is not possible to trace a single date of birth of SC. It is a recent discipline, born from the emotional studies in the psychological field of James (1955). James’ (1955) theories begin to recognize the centrality of emotions, in different experiences of human life, such as that of travel. Starting from this innovation and following the digital revolution, systematic studies were carried out on computational models that recognized emotions. The innovation of this approach lies precisely in reconsidering the relationship machine-man, able to program, not only artificial intelligence but especially "artificial emotional intelligence" (Papapicco, 2020). Picard (2000) identifies three types of emotional artificial intelligence with three different functions:

1. systems that detect the emotionality of users,
2. systems that express what human beings perceive as an emotional stimulus, and
3. systems that mimic the perception of emotionality.

This theoretical background will focus on the first type of systems or those that detect the emotionality of users. An example of these systems is the software that falls under the qualitative-quantitative methodology of SA. It is a methodology that is part of the approach of SC, useful to analyze texts to extract a polarity. SA is another multidisciplinary methodology, which will be treated from the field of computational psycho-linguistics.

Specifically, SA (Pang & Lee, 2008) is a methodology of analysis of texts that allows us to extract the subjectivity and the positive, negative or neutral polarity of a linguistic fact, allowing a better understanding of the users' opinion regarding service or product. From the textual data, in particular, it is possible to grasp feelings, emotions, opinions and judgments, or the private states of a person. It is necessary, however, a historical-conceptual distinction between opinion mining (OM) and SA. The expression OM appears for the first time in an article by Dave et al. (2003) published in 2003, according to which OM tools should process a set of information for a given item. The expression SA (Das & Chen, 2001; Tong, 2001), however, was initially used to indicate the evaluation of texts, from where it is possible to extract an emotional polarity (positive, negative, or neutral).

The terms SA and OM are, however, the same field of research and can be interchangeably used. The analysis of sentiment was born with Web 2.0, following the spreading blogs, social networking services (Facebook, Twitter, Youtube, etc.), other user-generated sites content (Amazon, Tripadvisor, Epinions, etc.) in which even non-expert users become content authors. Web 2.0 encloses digital natives (Prensky, 2001) of the years' ninety, who do not passively consume the information made available by the web but transform viewers (Pulcini, 2006) and commenters (Riva et al., 2015). Viewers are the users who modify or create existing content according to their own communicative needs; the commenters are digital natives who are not afraid to expose their opinions on blogs or social networks about specific issues.

These opinions of the digital natives of the generation Web 2.0 are a possible starting point for a SA, a methodology that uses the techniques of NLP, analyzing the textual sources based on semantic classification of words recognized as emotionally charged and the detection of sentiment polarity. Although SA has always aroused interest, it is in 2001 that greater awareness is reached about the issues and benefits of such an analysis methodology. The factors underlying this increased interest in SA are:

1. the increase in machine learning methods in the processing of natural language and information retrieval,
2. the availability of machine learning algorithms following the birth of the world wide web, and
3. the possibility of applying the results in different fields (Pang & Lee, 2008, p. 4-5).

On this basis, recent studies (Amplayo et al., 2018) show that machine learning is one of the most widely used methods in evaluating emotions in texts. On English-language Twitter data, Kaur et al. (2021) use a vector machine (SVM) as a hybrid methodology to detect and evaluate emotions from texts. Other approaches (Taboada et al., 2011), on the other hand, use the detection of emotions in texts through systems based on word dictionaries. The problem posed by scientific literature (Basiri et al., 2021) is that a dictionary-based approach is not enough to extrapolate sentiment from complex texts and, above all, in languages other than English. An example of a Turkish tweets study (Kirelli & Arslankaya, 2020) shows that it is necessary to produce its classification model.

To date, this methodology has many areas of application. SA applied to the tourism sector, for example, allows companies that deal with tourism to verify online presence and reputation, but especially CS, to assess the strengths and weaknesses of the service offered. There are also several tools to SA: the tools are based on algorithms that contain vocabulary of keywords that fall into a positive list, a negative and another neutral. The work of software is to make a match between text sources to be analyzed and inner vocabulary. The program of SA, therefore, facilitates the work of coding texts with sentiment detection. Conversely, making a SA is not always easy, because the authors of the texts in input express their emotions and opinions through a variety of sophisticated rhetorical strategies. A particularly fruitful application of SA concerns the world of social networks, including Twitter, a free social service networking and microblogging, to date one of the most famous and counts millions of users who make it use to inquire, to read opinions, to comment, to have/do followers (especially in political).

As is well known, this social network, which was born in 2006, allows users to post, at most 280 words. Opinions and comments are traceable through hashtags. Tweets help both tourists and tourist companies to gather short and valuable information (Atefeh & Khreich, 2015). Companies are increasingly using Twitter to measure CS (Alkubaisi et al., 2018) as data is always accessible and reachable. A peculiarity of Twitter is the possibility to find both profiles of users and companies and tourist locations: this is the case of Trenitalia, which will be taken into consideration here.

ITALIAN CASE OF TRENITALIA

In Italy, although lagging behind the rest of Europe, progress is being made towards the digitization of the tourism sector. An analysis of the individual Italian region's online reputation, conducted by researchers of the University of Marche (2015), showed the primacy of Tuscany both among Italian and foreign tourists. While the last places are the Valle d'Aosta and Trentino. Over 16,000 web conversations in Italian and English have been analyzed from which it emerged that Tuscany excels in both rankings and most of the content of the comments refer to the advantages of staying in Tuscany, that is the appreciation of typical food and wine, the charm of the natural beauty of the territory and the cultural heritage, the fundamental reason that drives tourists to visit the region. Calabria is particularly appreciated for the low cost of living, for the hospitality of its inhabitants and the fun, while the lack of information on public transport is a criticism to the region. In the Abruzzo region, however, the most positive comments concern the particularity of the territory and the high level of generosity and hospitality of the natives. Sardinia is mainly named for the beauty of the beaches, although it is recognized as the main attraction of the territory beauty; some users argue that Sardinia is also appreciable for its history. As far as Puglia is concerned, the main factors of appreciation concern the architectural beauty of the cities, such as squares, castles, churches and sanctuaries and there are numerous positive comments on the spectacular landscapes, the sea and the beaches. You can see, however, the low involvement of users regarding the two last regions in the ranking: the Valle d'Aosta in Italian conversations and Trentino Alto Adige in foreign ones. In particular, the reasons for which the two regions are positioned at the end of the ranking based on the qualitative-quantitative analysis carried out on the online conversations of tourists related to the fact that, for the Valle d'Aosta, A small number of conversations have been noted, and among the few comments analyzed is the evidence of negativity such as poor efficiency of public transport and infrastructure. It is also criticized for the decision to allow hunting on the weekend. For Trentino Alto Adige there are also a small number of conversations, where there are a low emotional impact and user involvement. "Digital tourism" is an increasingly important phenomenon, as can also be seen from data on sources of information for travel planning, according to which 74% of tourists travelling for leisure would use web searches to orient themselves in the choice of destinations. The current change in tourist mobility has not only occurred as a result of digitisation. Another key factor in the current transformation is the COVID-19 pandemic, which has placed restrictions on mobility, particularly tourism. Tourism is one of the most affected economic sectors.

From the point of view of companies, only a few tourism companies are using digital tools to measure their reputation, although some, such as Trenitalia, the transport company is pursuing digitalization as its business challenge. Trenitalia s.p.a. is an Italian rail transport company, born in 1905, under the name of "Ferrovie dello Stato". Addressing, in the labour market, the challenges of ethics, sustainability and technology, Trenitalia is provided with a website and related applications through which customers can buy tickets, receive information and even check train time and status. The mission of the company is precise to satisfy customers, developing for Italy a large mobility project (http://www.fsitaliane.it/fsi/Chi-Siamo/La-nostra-storia). Assuming that it is one of the first Italian companies to pursue the challenge of digitalization, what is the online reputation and satisfaction of tourists who use Trenitalia as a rail transport for holidays in pre-COVID-19 and COVID-19 periods?

Procedures and Hypothesis

This study, conducted on tweets posted by Twitter users, aims to examine how talks about the transport service offered by Trenitalia in two different touristic periods: pre-covid (summer 2019) and during the COVID-19 pandemic (summer 2020) in Italy. Another objective that the research aims to achieve is to prove that, based on the sentiment obtained (positive, negative, or neutral), companies can collect important information about the points of strength and weakness of your service or product and how it is important for the marketing strategies. In the case of Trenitalia, based on the tweets of users can identify, which aspects of the transport service satisfy customers, and which require improvements. To satisfy this objectives, the following research questions and hypothesis were formulated:

1. **RQ1:** How much the review of a tourist mobility service can be affected by the period in which you travel?
2. **RQ2:** Starting from the results of RQ1, we wondered if a mixed methodology of analysis of CS, i.e., SA, can be an optimal strategy to capture all the multidimensionality of the construct of CS.

Hypothesis

1. **H1:** There is a dependence between the calculated sentiment indicating the satisfaction of Trenitalia's customer and the travel period (pre-COVID-19 period vs. COVID-19 period).
2. **H2:** In case of dependence, this is not due to the case
3. **H3:** In case of non-random dependence, the mixed methodology can be a useful strategy to consider the multidimensionality of CS in tourist mobility.

To check the above assumptions, the tweets of Twitter were collected. The choice fell on this popular social because, in 280 characters maximum, provides the possibility to collect user opinions simply and immediately, thanks to hashtags and the setting of filters that search focused. In the study, were collected the tweets of users during the summer holidays of 2019 and 2020. Summer is one of the high tourist season periods in which travellers tend to organize holidays more frequently. The period taken into consideration goes from:

1. 1 July 2019 to 15 August 2019 for the summer season and
2. 1 July 2020 to 15 August 2020 for the summer season.

As for Trenitalia, were automatically collected tweets incorporating the Trenitalia hashtag. The hashtags chosen were: #Trenitalia; #viaggiaconTrenitalia; #vacanzeconTrenitalia (in the case of 2019: the pre-covid period) and the hashtag #restoinItalia (en translate #stayinItaly) or #vacanzeinItalia (en translate #holydaysinItaly) for the COVID-19 period 2020. The difference in the number of hashtags sought for the two years depends on the fact that, in 2020, for the period COVID-19, the Italian government has encouraged holidays in Italy, launching hashtags such as #stayinitaly or #holidaysinitaly. A first search using hashtags shows the lack of the same hashtags of 2019 in 2020. For this reason, we opted for tweets containing hashtags launched by the government.

The extraction took place through a Google Drive extension tool called "Twitter Archiver" and using the filter extraction system. Searching for tweets via hashtags, combined with content filtering, where the date was set, facilitated the search system. In particular, the filters used concerned the hashtag chosen as the search theme, the period with the dates specified in the dataset. Tweets posted from company pages or tweets containing only data have been excluded from the collection multimedia, such as videos or photos or content linked to other social networks, like Instagram. The extraction has produced, in the summer season, 674 tweets of 2019 and 100 tweets for 2020. It is necessary to specify that Social media users do not pay attention to spelling mistakes when sharing tweets, so the databases have been corrected manually, since the software matches between text and internal vocabulary.

Methodology

The methodology is the application of SA that produces quantitative and qualitative results. The use of mixed methodology through SA is related to this new focus on feelings of consumers as a new way to calculated CS (Sari et al., 2019). For the quantitative part, the tweets of the two seasons were combined for a comparison of the opinion and satisfaction of the service of Trenitalia between two years.

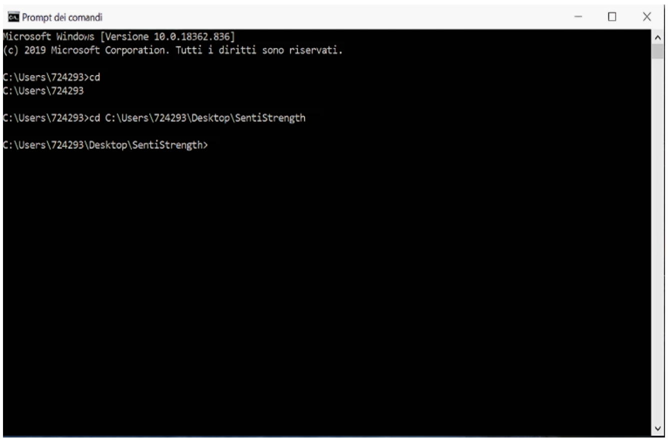

Figure 1. Command prompt, function to launch (Source: Author)

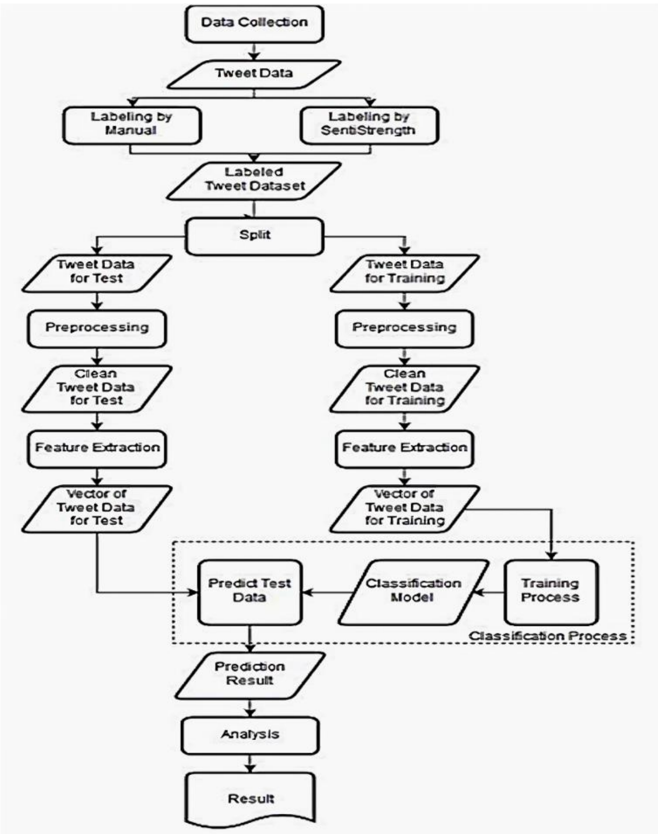

Figure 2. SentiStrength model (Prastowo & Yuniarno, 2019, p. 382)

This shows how SA is an effective mode of longitudinal monitoring of CS. SA was carried out automatically with the Sentistrength software (Prastowo & Yuniarno, 2019). SentiStrength is, therefore, a tool that allows us to calculate the sentiment and the analysis of the text directly from the internal function of the computer prompt commands, as shown in **Figure 1**.

The mode of operation of Sentistrength is to make a match between the input text, then the tweets of Trenitalia users collected in a file .csv, and the inner vocabulary. Technically, the operation of the software is shown in **Figure 2**, where the modelling of Prastowo and Yuniarno (2019) is reported.

Specifically, the model represents the representation of a training phase of the software. For the present research, it is interesting to note the phases of an automatic SA, summarized in:


BoosterWordList - Blocco note di Windows
File Modifica Formato Visualizza ?

```
alcuni	-1
assolutamente	1
cazzo	2
completamente	1
completo	1
così	0
dovrebbe	-1
dovrebbe	-1
enormemente	2
estremamente	2
fuckin	2
incredibilmente	2
leggermente	-1
molto	1
potrebbe	-1
potrebbe	-1
può	-1
sarebbe	-1
schiacciante	2
sicuramente	1
solo	-1
somma	-1
totale	1
totalmente	1
veramente	1
```

Figure 3. Some examples of booster words and their weight (Source: Author)

1. data collection of corpora (textual data),
2. stemming and data cleaning phase,
3. automatic analysis, and
4. results, or the conversion of the text into a score that indicates a polarity (positive, negative, or neutral), based on the match with the weight of the words present in the internal vocabulary.

The weight scale given to words in the internal vocabulary ranges from +5 to -5, where +5 is extremely positive and -5 extremely negative. The average scores indicate neutrality, understood as the absence of sentiment or mixed emotions in the same document (for example positive and negative in the same tweet). The score depends, therefore, on the vocabulary. Interesting is the reference to the headwords that make up the internal vocabulary. It must be specified that the vocabulary can be continuously updated, downloading them from the official website of Sentistrenght. There is a downloadable vocabulary for all languages, in this specific case, the Italian language will be used. Examples of internal vocabulary include booster words, emoticons, idioms, English words used in Italian, ironic terms, negations, question words, slang. An example of vocabulary and weight given to words is shown in **Figure 3**, where the vocabulary of booster words is reported.

The output is readable .txt file by converting it to Excel, where the polarity is returned for each document, with words highlighted in red for negative polarity, in green for positive polarity and in grey for neutrality. In the study, it is started from the polarity per year and two other quantitative aspects were studied, that is, the most frequent words used and the dependence of the polarity on the year, then on the historical period, or the context. These analyses were conducted with the statistical R software (Konietschke et al., 2015). To verify the dependence between the variables, the chi-square statistic has been applied. The frequency of words and the dependence between the variables is an important datum to analyze qualitatively the motivation of the polarity obtained with SA and, above all, in case of the dependence of the sentiment from the year, it is possible to reconstruct the context of the enunciation of the twitted text.

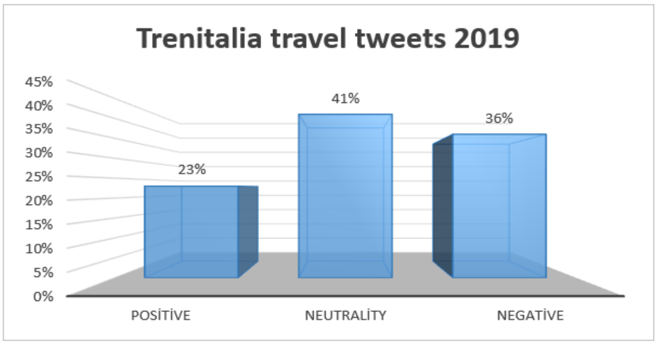

Figure 4. Output sentiment analysis tweets 2019 (Source: Author)

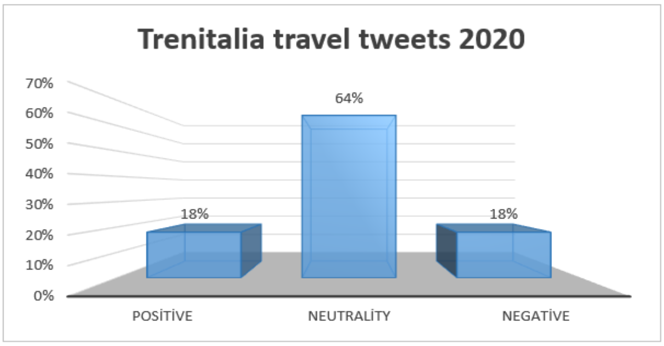

Figure 5. Output sentiment analysis tweets 2020 (Source: Author)

Table 1. Examples of negative, neutral and positive 2019 pre-COVID-19 tweets

Examples	Sentiment
Why #trenitalia decides to change the train numbers at random? To confuse people?	Negative
#trenitalia now I hate you every trip with you is a disgrace. What a pity that this time I could not book #italo!!	Negative
All I have to do is fix the last few things, and I can close the bags. I know that tomorrow I will arrive in Padua with my back in pieces, I know it, I feel it #vacanzeinitalia #trenitalia.	Neutral
Six of the morning. Train born in Rimini, announced to Pesaro with 20 minutes late. Thanks to #Trenitalia you always start well.	Neutral (given by contrast between positiveand negative polarity)
First birthday gift. Thank you #Trenitalia. We had great contrasts in the past, but I appreciate the gesture.	Positive

Table 2. Examples of negative, neutral, and positive 2020 COVID-19 tweets

Examples	Sentiment
On the train air conditioning ball and people without mask or better kept under the nose. Yes! #Fase2 #trenitalia #coronavirus #vacanzeinitalia.	Negative
Because one mask is not enough on #trenitalia #restoinitalia #vacanzeinitalia.	Neutral
… desert parking, empty compartment, train on schedule #vacanzeinitalia #trenitalia…	Positive

RESULTS

As for the results of SA, it can notice a prevalence of neutral polarity both in the tweets of 2019 and in those of 2020. A smaller gap between the polarities is noted in 2019, as can be seen from **Figure 4**.

As it can see from **Figure 4**, there is a 41% of neutrality, 36% of negativity and 23% of positivity for Trenitalia travel tweets 2019. Examples of negative, positive and neutral tweets for 2019 are represented in **Table 1**.

Also in the tweets of 2020, there is a prevalence of neutrality, but with greater disparity compared to negativity and positivity, which are found to have the same percentage, as shown in **Figure 5**.

As it can see from **Figure 5**, there is a 64% of neutrality, 18% of negativity and 18% of positivity for Trenitalia travel tweets 2020, as shown in the following examples for negative, neutral and positive tweets, reported in **Table 2**.

The presence of neutrality prevalence can be interpreted as the absence of sentiment or a mixed emotionality, composed of positivity and negativity in the same document. First of all, the comparison between the two years shows immediately the numerical difference between 2019 and 2020 in tweets posted to travel with Trenitalia. This additional element may depend both on the historical period and on the user's perception of the tweet read. Opinions on Twitter can reach a large number of people, namely other users. When, however, the audience is a company, therefore a body and not a user, a representation of the audience emerges from the Twitter user and the Trenitalia service. In this regard, Perelman and Olbrechts-Tyteca (1958) highlight the importance of the audience at the centre of the argument. The audience is a heterogeneous set of people, who have different beliefs, values, and expectations. For this reason, the speaker or the writer needs to know the audience and the means of communication used to hold on to the feelings of the recipients. The authors distinguish three types of audience:

a. the universal audience, whose members have different opinions and needs, often irreconcilable. He who speaks or writes, therefore, must show valid arguments of what he affirms and provide authentic motivations independent of space and time,

b. the audience formed by a single listener, these can actively participate in the argument or can be a silent subject; in this case, it can be universal or particular, and

c. the audience represented by the subject, it is the case in which the subject-to-argument presents to itself the reasons of its behaviour or tends to justify acts that can be the object of criticism.

In the case of Trenitalia, it is possible to hypothesize the existence of an audience formed by a single listener, that is the company, which is a silent subject. This may push users to consider the Twitter channel, not as a virtual place to communicate their satisfaction or dissatisfaction to reach the company itself, but a place to share with other users their satisfaction or dissatisfaction. Starting right from the prevalence of neutrality, it is necessary to understand what the context of enunciation within which tweets is are inserted. Using software R, the word frequencies of the year 2019 and the year 2020 were calculated. In the case of 2019, the most frequent word is "delay" ('*ritardo*'), as shown in **Figure 6**.

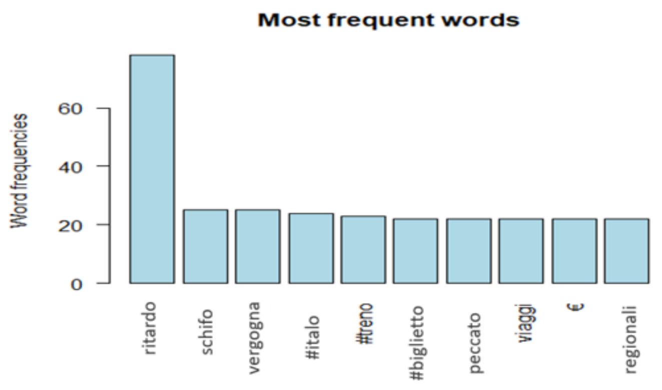

Figure 6. Most frequent words 2019 (Source: Author)

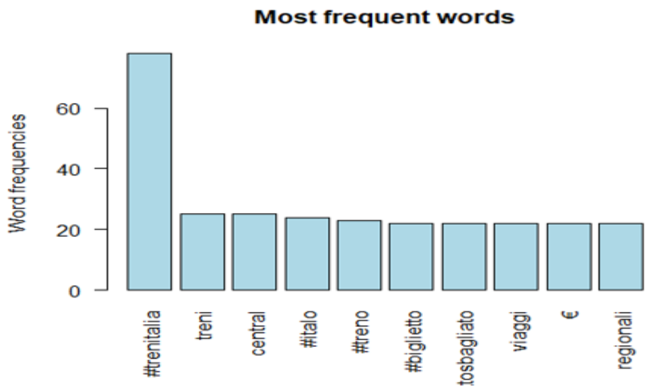

Figure 7. Most frequent words 2020 (Source: Author)

Other repeated words refer to moral aspects, such as "shame" ('vergogna') for the service provided and "disgust" ('schifo'). To shame and disgust, for example, the software attributed -4 as weight, so a pretty negative sentiment. From the frequencies of words of the year 2019 it can understand how the neutrality of sentiment, in reality, depends on mixed emotions present in the same document. In this case, in 2019, reference is made to the poor quality of service.

In 2020, however, the use of words more tending to neutrality, such as the hashtag "Trenitalia" or "trains" is noted, as shown in **Figure 7**.

It is interesting to note that the symbol of the euro is a frequent word both in 2019 and in 2020. It is a neutral word, as it is a symbol, especially if contextualized. Shooting the tweets where the symbol is contained, it can see that everyone is part of the trip in summer 2019 and 2020. In this period, users report the excessively expensive price of rail travel. Another common word is the "Italo" hashtag. Also in this case, the word is neutral, but contextualized again shows the negativity of the service offered by Trenitalia. The users, in any season in both years, announce that in the future they will prefer the service of Italo, a well-known Italian transport company, a competitor of Trenitalia.

In this regard, it is wondered if there is a dependence between the year (2019 and 2020) and polarity. In this part, the following assumptions have been made:

1. **H0:** The polarity is independent of the year and, therefore, from the context and
2. **H1:** The polarity is dependent on the year and, therefore, from the context.

Calculating $\chi 2$ shows the dependence of polarity on the period of writing tweets ($\chi 2[774]=17.99$; $p<.001$). This means that there is a significant difference in polarity according to 2019 and 2020. Verified the dependence of the results of SA concerning the years, we wonder if the observed difference is not due to chance but that, instead, there is a diversity between the averages of the sentiment of years (2019 and 2020).

1. **H0:** The polarity difference in years is due to the case and
2. **H1:** The polarity difference in years is not due to the case.

A paired sample t-test is then applied, with a comparison between the average polarity. The analysis returns a t-test value of 0.504, with df=98 and a p=0.01, which shows strong evidence to reject the null hypothesis. This result is interpreted as a difference in polarity in years not due to chance, confirming the significance of the $\chi 2$ result. This result confirms that the sentiment calculated by the software is significantly linked to the historical period lived and not to the service offered by Trenitalia. This quantitative figure has been explored qualitatively, since the software returns a neutral polarity in both cases, it is important to support quantitative analyses, with qualitative ones.

The analysis carried out provides for the identification of mitigation strategies on the results of Trenitalia. This is because tweets are linguistic facts of which it is necessary to know the operation considering the context and how the text is written. The context recalls the pragmatic dimension, while the ways of writing a tweet evoke the stylistic dimension. As in spoken language, even in the publication of tweets, users implement changes in the strengthening or attenuative direction, using the resources put to the provision by the natural language and by the social group of reference.

The opposite variation to accentuation or strengthening is mitigation (Caffi, 2013). The positive or negative value of both variations depends on the enunciation context, but the accentuation may be positive in case of empathic communications and may be negative in case of conflicts; mitigation, on the other hand, is useful in courtesy communications, but it can show a sense of speaker uncertainty. In particular, in the Trenitalia tweets it is possible to notice a greater presence of accentuation, but also a consistent number of mitigators falling within the functional technique: specifically, there is massive use of indicators of enunciative design (screens). Among the enunciative mitigation indicators, the most used is narrative and dramatization with the use of direct speech.

Example of the narrative is:

> "Capo Bonifati Cs. Stazione senza personale, nel mezzo del nulla. Sul regionale, capotreno fa pagare 5 euro di sovrattassa per bigl. #trenitalia [Capo Bonifati Cs. Station without staff, in the middle of nowhere. On the Regionale, capotreno charges 5 euro surcharge per ticket #trenitalia]."

Example of dramatization is:

> ""Biglietto per favore" "Tenga" "Non va bene" "Parli con la sua collega di Pescara. Questo m'ha dato". Il controllore se ne va. #Trenitalia ["Ticket please" "Here you are" "No good" "Talk to your colleague from Pescara. That gave me". The controller leaves. #Trenitalia]."

Another very numerous category in Trenitalia's tweets is that of the total substitutes, which are included in illocutor mitigation indicators (hedgerows). In particular, many rhetorical questions are used. Example of rhetorical questions is:

"Trenitalia sciopero nazionale la vergogna di essere italiana come voi. Mi da-te voi i soldi che perdo per non essere al lavoro? [Trenitalia national strike the shame of being Italian like you. Do you give me the money I lose for not being at work?]."

Much used by users is also the mitigation with the side effect, specifically, there are numerous strategies of fictionalization, that is, the entanglement of irony or parody of the current situation. Example of a restriction:

"Ringraziamo #trenitalia per questa sauna viaggiante–volgarmente detta "treno"- che ci ha fatto risparmiare il viaggio alle terme #mannaggiaate [We thank #trenitalia for this travelling sauna -commonly called "train"- that saved us the trip to the spa #mannaggiaate]."

The users, with these strategies, aim to obtain a cognitive and emotional detachment from the linguistic act. This would explain the recognition of neutrality as a prevalent sentiment. Starting from the reconstruction of the enunciation context, it is possible to notice differences between the two summer seasons. For example, although there is a high occurrence of the word 'shame' ('*vergogna*') both for the summer 2019, both for summer 2020, but with a lower frequency in 2019. The problems detected by Trenitalia users during the summer, such as excessive air conditioning of the carriages, they attenuate in the 2020 tweets. This may be due to the fact that, in 2020, air conditioning was not a major factor for travel. The decrease or absence of air conditioning was experienced as a lowering of the risk of getting sick and exchanging the symptoms of a possible cold with those of COVID-19.

The analysis of the context also reveals differences between one year and the next. 2019 has more tweets than trips with Trenitalia in the summer. In 2020, travel decreases due to the onset of the COVID-19 epidemic. This would explain the difference in the number of tweets in 2019 and 2020. In 2019, especially in the last period, there are tweets with a positive sentiment that refer to the beginning of sanitization and cleaning of trains, as shown in the following example:

"Finalmente #Trenitalia pulisce le carrozze ed inserisce i dispositivi di sicurezza, finalmente si viaggia #sicuri [Finally #Trenitalia cleans the coaches and inserts the safety devices, finally we travel #safe]."

Although the use of intensifiers, such as the repetition of "finally", loads the tweet of positivity, the meaning is not oriented to a positive message. The user states that Trenitalia is cleaning the coaches only after the beginning of what would have been a health emergency. This means that, in other periods, the carriages turn out to be dirty.

Based on these results, the mixed methodology has made it possible to understand that there are differences in the period of tourist mobility pre-COVID-19 and during COVID-19. The presence of veiled rhetorical strategies and mitigators in 2019, pre-COVID-19 period, indicate the intent of travellers to hit the Trenitalia service mainly with irony, for example:

"Un viaggio non è vero viaggio senza il disagio di #Trenitalia [A journey is not a real journey without the discomfort of #Trenitalia]."

In 2020, that is in the period COVID-19, instead, the negatively polarized issues have focused no longer on the service itself, but on non-compliance with the rules of personal protection (such as not wearing the mask or not wearing it properly). So, the focus of attention of travellers has shifted from the service itself to the responsibility of the company in enforcing the rules of personal protection.

In general, the results show that SA is a good methodology of analysis of the online reputation and CS of a company that deals with tourist mobility. One should, however, think of mixed methodologies (quantum-qualitative or which-quantitative) so that the result is understood by the company to identify the strengths and intervene on the weak points of the service. In particular, from this mixed methodology it is possible to note two cultural aspects concerning tourist mobility before and during the pandemic. The search for clean and cheap spaces are two important requirements present both in 2019 and in 2020. The need for safe travel, however, is accentuated in 2020 in which Italy was recovering from the period of the first wave of COVID-19 infections. Indeed, the safety and security need helped visitors to have greater trip satisfaction (Tasci & Boylu, 2010, p. 189).

DISCUSSION AND CONCLUSIONS

The digitization of tourism also leads to increased control by companies of their online presence, its online reputation, and CS, above all in a delicate period as the COVID-19 pandemic. SA is an innovative methodology that helps in the calculation of online reputation and CS, based on an emotional dimension of CS. Methodology, which is part of SC, allows extrapolating a polarity (positive, negative, or neutral) from textual data.

To assess the effectiveness of this methodology, the research is proposed the study of an Italian case, namely Trenitalia, a leading company in rail transport. This study, conducted on tweets posted by Twitter users, aims to examine how talks about the transport service offered by Trenitalia. Until now, traditional tools, such as questionnaires (Della Corte et al., 2015) or interviews (Koc, 2006), have always been used to detect CS in tourist mobility. Another objective that the research aims to achieve is to prove that, based on the sentiment (positive, negative, or neutral) companies can obtain important information about the points of strength and weakness of their service or product, monitoring two different periods. In the research, the following research questions and hypothesis were formulated:

1. **RQ1:** How much the review of a tourist mobility service can be affected by the period in which you travel?
2. **RQ2:** Starting from the results of RQ1, we wondered if a mixed methodology of analysis of CS, i.e., SA, can be an optimal strategy to capture all the multidimensionality of the construct of CS.

Hypothesis

1. **H1:** There is a dependence between the calculated sentiment indicating the satisfaction of Trenitalia's customer and the travel period (pre-COVID-19 period vs. COVID-19 period).
2. **H2:** In case of dependence, this is not due to the case.
3. **H3:** In case of non-random dependence, the mixed methodology can be a useful strategy to consider the multidimensionality of CS in tourist mobility.

A total of 674 tweets for the tourist season 2019 and 100 tweets for the tourist season 2020 were collected. The methodology is the application of SA that produces quantitative and qualitative results.

For the quantitative part, the sentiment was calculated first automatically via Sentistrength software, then an extraction of the frequencies and calculation of the dependence and significance (chi-square statistic and t-test statistic) between year and polarity was conducted with R, statistical software. From SA a prevalence of neutrality emerged in both 2019 and 2021 (41% vs. 64%). Neutrality, however, is linked to the presence of mixed emotions in the same document. It becomes, therefore, necessary, the frequencies' extraction to understand, which are the words most used by the users, and which have a positive or negative polarity. From the most frequent words, a prevalence of negativity emerges with the use of "shame" or "disgust" for 2019 and neutral words such as the symbol of the euro or references to the competitor company of Trenitalia. Even this reference, for example, although it is neutral, refers to a tweet in which, due to Trenitalia's failures, users report that they prefer the other transport company for their journeys. Based on these results, it is understood how important it is the context of enunciation within which sentiment fits **(RQ1)**. Starting from these findings, from the chi-square and t-test statistic results emerge the significant relevance of the historical period (context) in which the way of travel changes. This, however, makes it important to explore the data from a qualitative point of view. It is calculated the framework to verify the dependence of sentiment from the year (2019 and 2020), or the contextual historical period in which users tweet. It emerges, in fact, the dependence between sentiment and years of tourist mobility **(H1)** and this does not depend on a random calculation, but on the real dependence between year and CS **(H2)**. For this reason, it qualitatively reconstructs the meaning of the tweet starting from the intertwining between the text and the context, to understand the sentiment. The results of the qualitative analysis indicate the use of different mitigation strategies. The users, with these strategies, aim to obtain a cognitive and emotional detachment from the linguistic act. This would explain the recognition of neutrality as prevalent sentiment, but also the presence of an audience, such as the company, which on Twitter, turns out to be silent and not responsive. Besides, starting from the reconstruction of the enunciation context, it is possible to notice differences between the summer and the two touristic seasons. For example, although there is a high occurrence of the word 'shame' ('vergogna') both for 2019, both for 2019, but with a lower frequency in 2019 than in 2020. The problems detected by Trenitalia users during 2019, such as excessive air conditioning of the carriages, were attenuated in the tweets of the 2020 period. The analysis of the context also reveals differences between one year and the next. 2019 has more tweets than trips with Trenitalia in the summer. In the summer period of 2020 travel decreases due to the COVID-19 epidemic. The result can be interpreted either as a decrease in tourist mobility in 2020 linked to the period of restrictions of the pandemic or as a change of focus of customers from the service itself to failure to comply with the rules of individual protection. In contrast to studies on the relationship between emotionality and experience of using the tourist service (Loureiro & Kastenholz, 2011), which identify positive emotions related to satisfaction, this study shows that even negative emotional polarizations, like disgust, can be important results, if contextualized according to the historical period that determines the travel conditions.

Indeed, from the results, it is demonstrated that SA is a good methodology of analysis of the online reputation and CS of a company, like Trenitalia **(H3)**. One should, however, think of mixed methodologies (quanti-qualitative or quali-quantitative) so that the result of the study is understood by Trenitalia to identify the strengths and intervene on the weak points of the service. Getting a negative sentiment is not necessarily a sign of a bad reputation, but it becomes a means of understanding what the company needs to work on to offer a satisfactory service **(RQ2)**. However, the results obtained derive from the procedures of a SA software, which being based on a merely lexical analysis, has striking limitations by effect attribution of an incorrect sentiment to some meanings. It has been shown as a difficulty that the software algorithm might encounter in attributing sentiment by homonymous and ironic words. An example of an incorrect result regarding homographic words is the attribution of negative sentiment equal to -2 to the Italian word "mostri" ('show me'), in the imperative form of the verb "to show", confused with "mostri" ('monsters'). Rhetorical strategies such as irony or humour, however, are not recognized, as it is entrusted with a positive sentiment, while the communication intends to hit negatively: this should be a limit of SentiStrenght. In fact, in these cases of homography or veiled rhetorical strategies, the software does not attribute the right polarity. For this very reason, a mixed methodology becomes necessary, to recreate the connection to the enunciative context.

The attribution of the sentiment carried out by the tool turns out to be an automatic process and aseptic that prescinds from the recognition of equals in the graphic aspect but is different in the meaning. This study could provide a basis for future research perspectives. This it is proposed, for example, to try to analyze the same data with other software of SA, to evaluate how to eventually improve and customize vocabulary internal words or estimate the reliability in the recognition of terms and the attribution of sentiment in different software.

Finally, a strong point with research shows that SA is not a simple automatic methodology. Instead, it is a question of interpreting a numerical value by contextualizing it in the text. It is possible, in fact, to detect an important contextual difference between the two years, that is the need for security, culturally framed as "cleanliness" and "economy". This has practical implications, as, the Italian transport service can start from these values to satisfy its customers and improve tourist mobility. Working on the strengths and weaknesses of the service, traced with a quanti-qualitative methodology, becomes, for the torusit transport company, the topic on which to work for its marketing campaign. Beyond some inaccuracies in the calculation of sentiment, the limit exceeded with the qualitative deepening, the search has not introduced particular limits. Among the future prospects, there will surely be the application of SA with the aforementioned software with big data to evaluate the performance of the methodology in the calculation of CS.

Funding: The author received no financial support for the research and/or authorship of this article.

Ethics declaration: This article does not contain any studies with human participants or animals performed by the author.

Declaration of interest: The author declares no competing interest.

Data availability: Data generated or analyzed during this study are available from the author on request.

REFERENCES

Alkubaisi, G. A. A. J., Kamaruddin, S. S., & Husni, H. (2018). Stock market classification model using sentiment analysis on Twitter based on hybrid naive Bayes classifiers. *Computer and Information Science, 11*(1), 52-64. https://doi.org/10.5539/cis.v11n1p52

Amplayo, R. K., Lee, S., & Song, M. (2018). Incorporating product description to sentiment topic models for improved aspect-based sentiment analysis. *Information Sciences, 454,* 200-215. https://doi.org/10.1016/j.ins.2018.04.079

Ardani, W., Rahyuda, K., Giantari, I. G. A. K., & Sukaatmadja, I. P. G. (2019). Customer satisfaction and behavioral intentions in tourism: A literature review. *International Journal of Applied Business and International Management, 4*(3), 84-93. https://doi.org/10.32535/ijabim.v4i3.686

Atefeh, F., & Khreich, W. (2015). A survey of techniques for event detection in twitter. *Computational Intelligence, 31*(1), 132-164. https://doi.org/10.1111/coin.12017

Barsky, D. (1992). Customer satisfaction in the hotel industry: Meaning and ieasurement. *Hospitality Research Journal, 16*(1), 51-73. https://doi.org/10.1177/109634809201600105

Basiri, M. E., Nemati, S., Abdar, M., Cambria, E., & Acharya, U. R. (2021). ABCDM: An attention-based bidirectional CNN-RNN deep model for sentiment analysis. *Future Generation Computer Systems, 115*, 279-294. https://doi.org/10.1016/j.future.2020.08.005

Caffi, C. (2013). Mitigation. In M. Sbisà, & K. Turner (Eds.), *Pragmatics of speech actions* (pp. 257). De Gruyter Mouton. https://doi.org/10.1515/9783110214383.257

Cambria, E., & Hussain, A. (2012). *Sentic computing: Techniques, tools, and applications*. Springer. https://doi.org/10.1007/978-94-007-5070-8

Campo, S., & Yagüe, J. M. (2009). Exploring non-linear effects of determinants on tourists' satisfaction. *International Journal of Culture, Tourism and Hospitality Research, 3*(2), 127-138. https://doi.org/10.1108/17506180910962131

Campo-Martínez, S., & Garau-Vadell, J. B. (2010). The generation of tourism destination satisfaction. *Tourism Economics, 16*(3), 461-475. https://doi.org/10.5367/000000010792278383

Cavazza, N. (2012). *Pettegolezzi e reputazione* [*Gossip and reputation*]. Il Mulino.

Chang, J. C. (2008). Tourists' satisfaction judgments: An investigation of emotion, equity, and attribution. *Journal of Hospitality and Tourism Research, 32*(1), 108-134. https://doi.org/10.1177/1096348007309571

Chatzigeorgiou, C., Christou, E., Kassianidis, P., & Sigala, M. (2009). Examining the relationship between emotions, customer satisfaction and future behavioural intentions in agrotourism. *Tourismos: An International Multidisciplinary Journal of Tourism, 4*(4), 145-161.

Chen, C. F., & Chen, F. S. (2010). Experience quality, perceived value, satisfaction and behavioral intentions for heritage tourists. *Tourism Management, 31*(1), 29-35. https://doi.org/10.1016/j.tourman.2009.02.008

Choi, T. Y., & Chu, R. (2001). Determinants of hotel guests‟‟ satisfaction and repeat patronage in the Hong Kong hotel industry. *International Journal of Hospitality Management, 20*(3), 277- 297. https://doi.org/10.1016/S0278-4319(01)00006-8

Das, S., & Chen, M. (2001). Yahoo! for Amazon: Extracting market sentiment from stock message boards. In *Proceedings of the Asia Pacific Finance Association Annual Conference.*

Dash, G., Kiefer, K., & Paul, J. (2021). Marketing-to-millennials: Marketing 4.0, customer satisfaction and purchase intention. *Journal of Business Research, 122*, 608-620. https://doi.org/10.1016/j.jbusres.2020.10.016

Dave, K., Lawrence, S., & Pennock, D. M. (2003). Mining the peanut gallery: Opinion extraction and semantic classification of product reviews. In *Proceedings of WWW* (pp. 519-528). https://doi.org/10.1145/775152.775226

De Kerckhove, D. (2003). *La conquista del tempo. Società e democrazia nell'era della rete* [*The conquest of time. Society and democracy in the Internet age*]. Editori Riuniti.

Deaden, P., & Harron, S. (1994). Alternative tourism and adaptive change. *Annals of Tourism Research, 21*(1), 81-102. https://doi.org/10.1016/0160-7383(94)90006-X

Della Corte, V., Sciarelli, M., Cascella, C., & Del Gaudio, G. (2015). Customer satisfaction in tourist destination: The case of tourism offer in the city of Naples. *Journal of Investment and Management, 4*(1-1), 39-50. https://doi.org/10.11648/j.jim.s.2015040101.16

Deng, W. J., Yeh, M. L., & Sung, M. L. (2013). A customer satisfaction index model for international tourist hotels: Integrating consumption emotions into the American customer satisfaction index. *International Journal of Hospitality Management, 35*, 133-140. https://doi.org/10.1016/j.ijhm.2013.05.010

Fah, L. K., & Kandasamy, S. (2011). An investigation of service quality and customer satisfaction among hotels in Langkawi. In *Proceedings of the International Conference on Management.*

Ginieis, M., Sánchez-Rebull, M-V., & Campa-Planas, F. (2012). The academic journal literature on air transport: Analysis using systematic literature review methodology. *Journal of Air Transport Management, 19*, 31-35. https://doi.org/10.1016/j.jairtraman.2011.12.005

Gountas, J., & Gountas, S. (2007). Personality orientations, emotional states, customer satisfaction, and intention to repurchase. *Journal of Business Research, 60*(1), 72-75. https://doi.org/10.1016/j.jbusres.2006.08.007

Gui, M. (2014). *A dieta di media* [*On a medium diet*]. Il Mulino.

Gummesson, E. (1998). *Relationship marketing as a paradigm shift: Some conclusions from the 30R approach. Management Decision, 35*(3-4), 267-272. https://doi.org/10.1108/00251749710169648

Hoyer, W. D., & MacInnis, D. J. (2001). Consumer behaviour. Houghton Mifflin Company.

Huang, H. H., Chiu, C. K., & Kuo, C. (2006). Exploring customer satisfaction, trust and destination loyalty in tourism. *Journal of American Academy of Business, 10*(1), 156-159. https://doi.org/10.1108/BIJ-04-2015-0038

Hult, G. T. M., Sharma, P. N., Morgeson III, F. V., & Zhang, Y. (2019). Antecedents and consequences of customer satisfaction: do they differ across online and offline purchases? *Journal of Retailing, 95*(1), 10-23. https://doi.org/10.1016/j.jretai.2018.10.003

Hwang, J., & Han, H. (2014). Examining strategies for maximizing and utilizing brand prestige in the luxury cruise industry. *Tourism Management, 40*, 244-259. https://doi.org/10.1016/j.tourman.2013.06.007

Iaquinto, B. L. (2020). Tourist as vector: Viral mobilities of COVID-19. *Dialogues in Human Geography, 10*(2), 174-177. https://doi.org/10.1177/2043820620934250

James, W. (1955). *Pragmatism*. Merridian Books.

Kaur, H., Ahsaan, S. U., Alankar, B., & Chang, V. (2021). A proposed sentiment analysis deep learning algorithm for analyzing COVID-19 tweets. *Information Systems Frontiers, 13*, 1417-1429. https://doi.org/10.1007/s10796-021-10135-7

Kirelli, Y., & Arslankaya, S. (2020). Sentiment analysis of shared tweets on global warming on Twitter with data mining methods: A case study on Turkish language. *Computational Intelligence and Neuroscience, 2020*, 1904172.https://doi.org/10.1155/2020/1904172

Koc, E. (2006). Total quality management and business excellence in services: The implications of all-inclusive pricing system on internal and external customer satisfaction in the Turkish tourism market. *Total Quality Management & Business Excellence, 17*(7), 857-877. https://doi.org/10.1080/14783360600595252

Konietschke, F., Placzek, M., Schaarschmidt, F., & Hothorn, L. A. (2015). nparcomp: An R software package for nonparametric multiple comparisons and simultaneous confidence intervals. *Journal of Statistical Software, 64*(9), 1-17. https://doi.org/10.18637/jss.v064.i09

Lee, K.-W., Kim, H.-B., Kim, H.-S., & Lee, D.-S. (2010). The determinants of factors in FIT guests' perception of hotel location. *Journal of Hospitality and Tourism Management, 17*(1), 167-174. https://doi.org/10.1375/jhtm.17.1.167

Leingpibul, T., Thomas, S. Broyles, A., & Ross R. H. (2009). Loyalty's influence on the consumer satisfaction and (re)purchase behavior relationship. *Journal of Consumer Satisfaction: Dissatisfaction and Complaining Behavior, 22*, 36-53.

Lindberg, K., & Johnson, R. L. (1997). The economic values of tourism's social impacts. *Annals of Tourism Research, 24*(1), 90-116. https://doi.org/10.1016/S0160-7383(96)00033-3

Lindberg, K., Andersson, T. D., & Dellaert, B. G. (2001). Tourism development: Assessing social gains and losses. *Annals of Tourism Research, 28*(4), 1010-1030. https://doi.org/10.1016/S0160-7383(01)00007-X

Loureiro, S. M. C. (2010). Satisfying and delighting the rural tourists. *Journal of Travel and Tourism Marketing, 27*(4), 396-408. https://doi.org/10.1080/10548408.2010.481580

Loureiro, S. M. C., & Kastenholz, E. (2011). Corporate reputation, satisfaction, delight, and loyalty towards rural lodging units in Portugal. *International Journal of Hospitality Management, 30*(3), 575-583. https://doi.org/10.1016/j.ijhm.2010.10.007

Manuti, A., Cortini, M., & Mininni, G. (2007). La costruzione discorsiva della meta nelle campagne di promozione turistica [The discursive construction of the destination in tourism promotion campaigns]. *Turismo e Psicologia* [*Tourism and Psychology*], *1*(1), 116-127.

Martin, D. S., & O'Neill, M. (2010). Scale development and testing: A new measure of cognitive satisfaction in sports tourism. *Event Management, 14*(1), 1-15. https://doi.org/10.3727/152599510X12724735767471

McIntosh, R., & Goeldner, C. (1984). *Tourism: Principles, practice, philosophies*. Grid Publication.

Mereu, A. (2004). La psicologia del turismo [The psychology of tourism]. *HT Psico-Pratika* [*HT Psycho-Practice*], *11*, 1-3.

Mereu, A. (2010). La motivazione al turismo [Motivation for tourism]. *HT Psico-Pratika* [*HT Psycho-Practice*], *16*, 1-4.

Molinari, L., Abratt, R., & Dion, P. (2008). Satisfaction, quality, and value and effects on the repurchase and positive word of mouth behavioural intentions in a business to business services context. *Journal of Services Marketing, 22*(5), 363-373. https://doi.org/10.1108/08876040810889139

Motlagh, A. T., Sadeh, E., Sadeh, S., Jafari, H., Morovat, J. A., & Enaamzadeh A. (2013). How does service quality lead to loyalty in the hotel industry in Iran. *Research Journal of Applied Sciences, Engineering and Technology, 5*(2), 347-379. https://doi.org/10.19026/rjaset.5.4961

Nowak, J., & Sahli, M. (2007). Coastal tourism and "Dutch disease" in a small island economy. *Tourism Economics, 13*(1), 49-65. https://doi.org/10.5367/000000007779784452

Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval, 2*(1-2), 1-135. https://doi.org/10.1561/1500000011

Papapicco, C. (2020). Google mini: Italian example of artificial prosociality. *Online Journal of Communication and Media Technologies, 10*(3), e202015. https://doi.org/10.29333/ojcmt/7995

Perelman, C., & Olbrechts-Tyteca, L. (1958). *Trait de l'argumentation. La nouvelle rhettorique* [*Line of argument. The new rhetoric*]. Presses Universitaires de France.

Peverini, P. (2014). Environmental issues in unconventional social advertising: A semiotic perspective. *Semiotica, 199*, 219-246. https://doi.org/10.1515/sem-2013-0126

Picard, R. W. (2000). Toward computers that recognize and respond to user emotion. *IBM Systems Journal, 39*(3-4), 705-719. https://doi.org/10.1147/sj.393.0705

Prastowo, E. Y., & Yuniarno, E. M. (2019). Combining SentiStrength and multilayer perceptron in Twitter sentiment classification. In *Proceedings of the 2019 International Seminar on Intelligent Technology and Its Applications* (pp. 381-386). https://doi.org/10.1109/ISITIA.2019.8937134

Prensky, M. (2001). Digital natives, digital immigrants. *On the Horizon, 9*(5), 1-6. https://doi.org/10.1108/10748120110424843

Pulcini, E. (2006). *Click TV. Come Internet e il digitale cambieranno la television* [*Click TV. How the Internet and digital will change television*]. Franco Angeli.

Rathnayake, M. (2015). How does 'crowding' affect visitor satisfaction at the Horton Plains National Perk in Sri Lanka? *Tourism Management Perspectives, 16*, 129-138. https://doi.org/10.1016/j.tmp.2015.07.018

Ravishankar, B., & Christopher, P. B. (2020). Impact of innovative services on customer satisfaction and enhancing tourism: airline and hotel services from a tourist perspective. *Journal of Critical Reviews, 7*(11), 705-711.

Riva, G., Wiederhold, B. K., & Cipresso, P. (2015). Psychology of social media: From technology to identity. In G. Riva, B. K. Wiederhold, & P. Cipresso (Eds.), *The psychology of social networking: Personal experience in online communities* (pp. 1-11). De Gruyter Open. https://doi.org/10.1515/9783110473780

Sánchez-Rebull, M. V., Rudchenko, V., & Martín, J. C. (2018). The antecedents and consequences of customer satisfaction in tourism: a systematic literature review. *Tourism and Hospitality Management, 24*(1), 151-183. https://doi.org/10.20867/thm.24.1.3

Sari, E. Y., Wierfi, A. D., & Setyanto, A. (2019). Sentiment analysis of customer satisfaction on transportation network company using naive Bayes classifier. In *Proceedings of the 2019 International Conference on Computer Engineering, Network, and Intelligent Multimedia* (pp. 1-6). IEEE. https://doi.org/10.1109/CENIM48368.2019.8973262

Sharma, G. D., Thomas, A., & Paul, J. (2021). Reviving tourism industry post-COVID-19: A resilience-based framework. *Tourism Management Perspectives, 37*, 100786. https://doi.org/10.1016/j.tmp.2020.100786

Smith, S. L. (1998). The tourism product. *Annals of Tourism Research, 21*, 582-595. https://doi.org/10.1016/0160-7383(94)90121-X

Taboada, M., Brooke, J., Tofiloski, M., Voll, K., & Stede, M. (2011). Lexicon-based methods for sentiment analysis. *Computational Linguistics, 37*(2), 267-307. https://doi.org/10.1162/COLI_a_00049

Tasci, A. D., & Boylu, Y. (2010). Cultural comparison of tourists' safety perception in relation to trip satisfaction. *International Journal of Tourism Research, 12*(2), 179-192. https://doi.org/10.1002/jtr.745

Tong, R. M. (2001). An operational system for detecting and tracking opinions in on-line discussions. In *Proceedings of the Working Notes of the ACM SIGIR Workshop on Operational Text Classification* (pp. 1-6).

Torre, A., & Scarborough, H. (2017). Reconsidering the estimation of the economic impact of cultural tourism. *Tourism Management, 59*, 621-629. https://doi.org/10.1016/j.tourman.2016.09.018

van Raaij, W. F., & Francken, D. A. (1984). Vacation decisions, activities, and satisfactions. *Annals of Tourism Research, 11*(1), 101-112. https://doi.org/10.1016/0160-7383(84)90098-7

Zhang, Z., Ye, Q., Song, H., & Liu, T. (2014). The structure of customer satisfaction with cruise-line services: An empirical investigation based on online word of mouth. *Current Issues in Tourism, 18*(5), 450-464. https://doi.org/10.1080/13683500.2013.776020

Zhou, L., Ye, S., Pearce, P. L., & Wu, M. (2014). Refreshing hotel satisfaction studies by reconfiguring customer review data. *International Journal of Hospitality Management, 38*, 1-10. https://doi.org/10.1016/j.ijhm.2013.12.004

❖❖❖