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Master in Computer Science and Business Management

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TECNOLOGIAS
E ARQUITETURA

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Acknowledgements

Writing this dissertation, just like a flight, was a journey where I had the opportunity to broaden my horizons, step out of my comfort zone, deal with a turbulence of emotions and challenges to, ultimately, achieve a place I thought I would never reach. COVID-19 made this journey specially challenging but, in a weird way, it is also the reason why this study exists.

This dissertation was made possible by several people, to which I would like to thank.

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Resumo

A pandemia COVID-19 trouxe muitos desafios à indústria da aviação, resultando em drásticas alterações à experiência dos passageiros. O objetivo deste estudo é compreender as diferenças na satisfação dos passageiros, antes e depois da pandemia COVID-19, bem como quais os fatores que a influenciam. A amostra consiste em 9745 comentários deixados por passageiros no conhecido site de comentários, airlinequality.com, cujo proprietário é a SKYTRAX. Os comentários foram analisados recorrendo a uma ferramenta de análise de sentimentos, especialmente calibrada para a indústria aeronáutica, de modo a obter resultados mais precisos. Os resultados sugerem que os passageiros não estavam satisfeitos com as companhias aéreas, e esse sentimento foi agravado durante a pandemia. O comportamento dos trabalhadores das companhias aéreas são o fator que mais influencia a satisfação dos passageiros. A principal conclusão é que os passageiros, após a pandemia, demonstram preocupações acrescidas com reembolsos e com a limpeza da cabine das aeronaves. Este estudo mostra que análise de comentários de passageiros é uma forma eficiente de recolher a opinião dos clientes, dando oportunidade às companhias aéreas de melhorarem continuamente os seus serviços.

Palavras-Chave: satisfação de clientes; análise de sentimentos; companhias aéreas; COVID-19;

Abstract

The COVID-19 pandemic brought many challenges to the airline industry, resulting in radical changes to the passengers' experience. The purpose of this study is to understand the differences in customer satisfaction between the pre-COVID-19 period and during the COVID-19 pandemic, as well the factors that influence said satisfaction. The sample of this study consists of a dataset with 9,745 reviews written by passengers on the well-known airline reviews website, airlinequality.com, owned by SKYTRAX. The reviews were analyzed with a sentiment analysis tool that was specially calibrated for the aviation industry to be more accurate. The findings of this study show that passengers were unhappy with airlines before the pandemic, and those feelings were aggravated after the COVID-19 outbreak. The behavior of airline staff is the main factor to influence passengers' satisfaction. The main takeaway is that passengers, after the pandemic, are mostly worried with refunds and aircraft cabin cleanliness. This study shows that analyzing passenger reviews is an effective way of gathering customer feedback, paving the way for airlines to continuously improve their service offerings.

Keywords: customer satisfaction; sentiment analysis; airlines; COVID-19;

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Chapter 1 – Introduction

1.1. Contextualization

The sudden outbreak caused by the novel coronavirus has brought to many industries unprecedented challenges, impacting severely, as Monmousseau et al. (2020) mention, the commercial aviation industry. The impact can be explained due to the strict travel restrictions that are being imposed by several countries to diminish the spread of the virus (Monmousseau et al., 2020). As the disease spread worldwide, everything from business to schools moved towards online alternatives, travel restrictions were put in place, unemployment rates skyrocketed, and people became uneasy about traveling due to the highly contagious nature of the virus. Air travel began to dramatically drop throughout the globe by mid-March 2020 (Iacus et al., 2020), with seat availability dropping as much as 90% in April when compared to the same period last year (Suau-Sanchez et al., 2020). In a matter of months, the pandemic brought the aviation industry to a standstill, and airlines worldwide faced huge revenue losses (Hotle & Mumbower, 2021).

According to industry leaders, thanks to the indefinite timeline for the end of social distancing and travel restrictions, much uncertainty remains on how long the pandemic will endure and how long until the air transportation sector recovers (Sobieralski, 2020). However, it is expected that the impacts are for the long-term and recovery is to take at least three to six years. Whether it will take three or six years until airlines recover, there is a need to understand what is happening and what might occur to airlines in order to prepare themselves to adjust to the uncertain future that lies ahead (Tuchen et al., 2020).

1.2. Motivation

Nowadays, the airline industry has become a place where fierce competition is the norm. To survive and distinguish from each other, airlines are required manage their passengers' relations effectively to guarantee and retain customer satisfaction, with the ultimate goal of driving future income (Sezgen et al., 2019). Siering et al. (2018) go as far as saying that for corporations, customer feedback, in particular, is a critical factor for business growth and performance but mainly for product and service innovation and also for improving customer experience. With that in mind, not only it is important to understand how passengers evaluate airlines, but also to identify which dimensions of satisfaction are the most important for passengers (Park et al., 2004).

Thanks to social media, the production of data is increasing at an exponential rate, mainly through posts and comments, say Sternberg et al. (2018). As a result, big data has become a valuable resource that, when analyzed, enables companies to better understand the behavior of their customers (Sternberg et al., 2018). Therefore, websites like TripAdvisor, that focus on gathering online reviews from restaurants, hotels, and, more recently, airlines, are a comprehensive source of high-quality, spontaneous data ready to be analyzed (Rane & Kumar, 2018).

Online reviews, however, typically appear as unstructured text, frequently regarding several experiences and opinions concerning different aspects or topics of the reviewed product or service. This goes to say that seldomly reviewers write their reviews in a standardized manner which, in turn, makes it difficult for corporations to understand their customers' satisfaction (Siering et al., 2018).

With the existence of user-generated content (online reviews, for example), allied with new technologies, researchers are now able to get to know travelers' perceptions and their level of satisfaction through sentiment analysis, even if the text is unstructured (Alaei et al., 2019). Sentiment analysis is able to determine the overall polarity of sentiment in reviews, text documents, and so forth. Polarity can then be classified as positive, negative, or neutral (Sternberg et al., 2018). Although sentiment analysis has proven to be highly relevant for the tourism industry, it only started to gain popularity until recently (Guo et al., 2017; Lacic et al., 2016; Zhang et al., 2016).

1.3. Research purpose

During pandemic situations, it is essential to understand and study, from various perspectives, the air transportation system (Monmousseau et al., 2020). For example, studies have address how diseases propagate inside airplanes (Namilae et al., 2017) and how the pandemic and its travel restrictions affected airline employment (Sobieralski, 2020). However, to the best of the author's knowledge, no study in the literature assesses how the changes brought by the COVID-19 pandemic affected the passengers' travel experience so far, mainly their satisfaction towards airlines. With that in mind, we aim to understand the differences in customer satisfaction between the pre-COVID-19 period and during the COVID-19 pandemic. Moreover, we intend to discover what factors influence customer satisfaction then and now.

To achieve the proposed objective, customer feedback must be gathered from passengers who have flown before and during the pandemic. One way that we (and airlines altogether) can gather customer feedback is through questionnaires and forms (Guo et al., 2017). Although it is a perfectly acceptable way of gathering customer feedback, Rane and Kumar (2018) mention that these tend to be very time-consuming and often involve lots of human resources that come at a cost in analyzing them. They add saying that the information collected from the questionnaires is often inaccurate and inconsistent because people do not enjoy filling forms or do not have the patience to take the surveys seriously.

With that in mind, we will be collecting online reviews from the Air Travel review website[1], which is the top review site for airport, airline and associated air travel traveler reviews (Skytrax, 2021a). It is worth mentioning that the website explicitly says that has no financial association with the airports and airlines featured. Furthermore, the website is owned by Skytrax, which is a brand-name known worldwide for its Airline and Airport Star Rating, the World Airline Awards and Airport Awards (Skytrax, 2021a).

The reviews will be collected before the COVID-19 period and during the COVID-19 period. Once the data is collected, through the text mining tool Semantria, we will analyze the extracted reviews. The tool, which will be calibrated with an aviation specific dictionary to improve accuracy, will be able to identify the most mentioned satisfaction

[1] www.airlinequality.com

dimensions by the passengers and measure the sentiment polarity of each review (Lexalytics.com, 2021a, 2021c).

Finally, once we analyze the results, we will be able to answer the objectives of this research. Additionally, it is expected that with the gathered information it will be possible for airline's stakeholders to better understand the market and their customers, adjust accordingly to these uncertain times and make long-term decisions.

1.4. Dissertation structure and organization

The present study is organized in four chapters, reflecting the different phases of the research until its conclusion. The chapters are Introduction, Literature review, Methodology, Results and discussion, Conclusion.

An integrative review is performed in the next chapter to understand the state-of-the-art regarding customer satisfaction in the airline industry. The Methodology chapter follows where the research method is explained, including data collection. The next chapter, Results and Discussion, presents and explains the findings. Finally, the Conclusion chapter follows where a conclusion is drawn, implications and limitations are described and suggestions for future studies are made.

Chapter 2 – Literature Review

In this section, an integrative review is performed. The research gap for this review is explained, as well as the steps that were taken to perform it. The findings are then reported.

2.1.The need for a review

An integrative review is a good method to summarize information about a specific topic. Since the main purpose of this dissertation is to understand how the COVID-19 pandemic affected airline passengers' satisfaction, it is necessary to understand how the satisfaction was distributed along its different dimensions before the pandemic started. It is also important to discover if any work has been done on understanding passenger satisfaction during the pandemic. Those are the objectives of the present review.

Since this dissertation will use text mining techniques such as sentiment analysis, it would make sense to research previous works that used similar techniques. To assess the work done regarding the current topic, before and during the pandemic, two integrative reviews are performed, one for each timeline.

Integrative Review 1 (IR1) – It has the objective of assessing what work has been done regarding analyzing customer satisfaction towards airlines, using text mining techniques, during the pre-pandemic period (2015-2020).

Integrative Review 2 (IR2) – It has the objective of assessing what work has been done regarding analyzing customer satisfaction towards airlines retrieved from online sources, using text mining techniques, during the pandemic period (2020-2021).

2.2.IR1

2.2.1. Review protocol

To perform this integrative review, several databases were used, namely IEEE, Web of Science and EBSCO to get the maximum number of papers that could address the proposed research questions. The search string used was “Airline AND Satisfaction AND (Mining OR Sentiment)”. Only articles from 2015 to 2020 were considered, as we considered this to be the ideal interval to get relatively recent papers until the pandemic. The articles were searched between January 6th, 2021 and January 7th, 2021. Then, the results obtained in the search were filtered with the following criteria (Table 1).

Table 1 - *Filters*

Filter name	Criteria
F1	Keywords searched on full text.
F2	Keywords searched only in the abstract
F3	Duplicate documents are removed

Inclusion criteria were applied to retrieve articles that better suit the research objectives. Table 2 shows the applied criteria.

Table 2 - *Inclusion criteria*

Inclusion criteria
Peer-reviewed articles
Articles from Academic journals or conferences
Articles in English
Articles available online

2.2.2. Conducting the review

This section corresponds to the second step of the IR. The review protocol, described previously, has been applied. The summarization of the results follows.

Table 3 summarizes the keywords used for each database and the filters applied to the search results.

Table 3 - *Documents obtained based on filter application for RQ1*

DB	Keywords	F1 - Full Text	F2 - Only Abstract	F3 - Duplicates Removal
IEEE Xplore	Airline AND Satisfaction AND Mining	6	2	2
	Airline AND Satisfaction AND Sentiment	4	3	2
Web of Science	Airline AND Satisfaction AND Mining	57	2	2
	Airline AND Satisfaction AND Sentiment	58	8	3
EBSCO	Airline AND Satisfaction AND Mining	12658	7	4
	Airline AND Satisfaction AND Sentiment	7862	6	3
	Total	**20645**	**28**	**16**

Afterward an exclusion criterion was applied to the set of papers to assess if the content was relevant for this review and, only then, the final set was obtained. From the initial 16 papers, only 11 were relevant.

2.2.3. Sample characteristics

In this section, a statistical analysis was performed to understand the paper's distribution over the years and where their origin from. The distribution of the type of documents used can be seen in Figure 1. It is shown that half of the documents originate from Journals, and the other half from Conference proceedings.

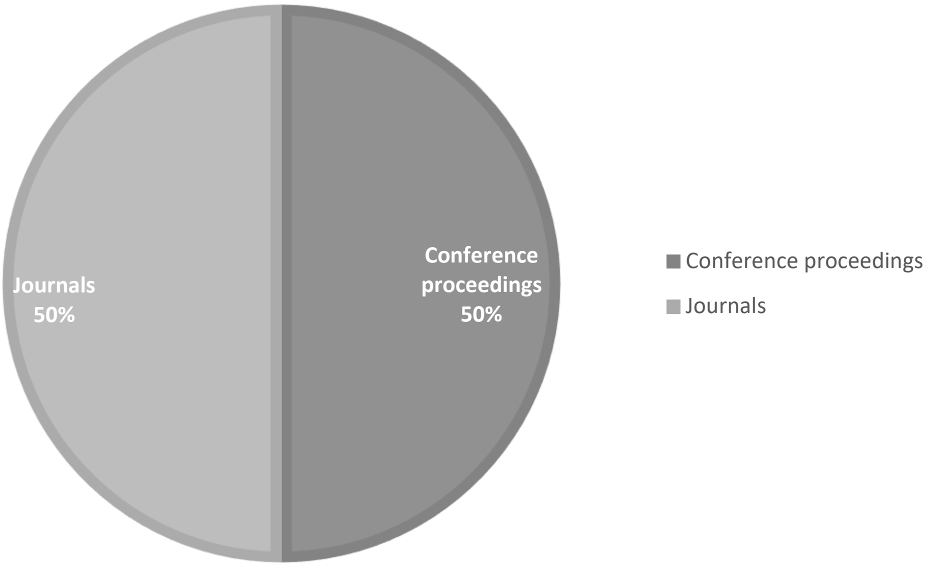

Fig. 1 - *Document type distribution for IR1*

Figure 2 shows the distribution of the papers by year. Over the years a rise in the number of papers is noted, suggesting a growing popularity regarding the present theme of this paper, until a decline in 2020, probably due to the COVID-19 pandemic.

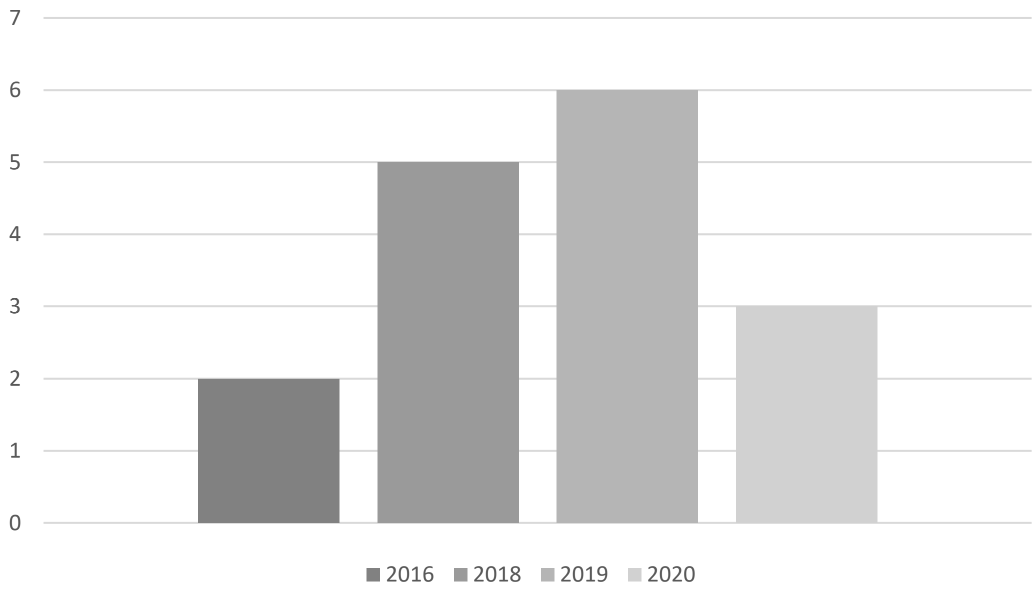

Fig. 2 - *Document distribution by year for IR1*

2.2.4. Report

Table 4 summarizes the information retrieved in articles found. It shows the authors of the article, a brief explanation of their findings, and what technologies were used, such as the text mining technique, the website that was used as source, the name type of WebCrawler, the tools that were used for sentiment analysis and, finally, the size of the sample collected.

Table 4 - *Summary of the articles found*

Literature	Findings	Text Mining Technique	Website used	WebCrawler used	Tool used for sentiment analysis	Sample size
(Sezgen et al., 2019)	Explored how satisfaction varies among traveling class; Friendliness and helpfulness, service and low fares are the most critical dimensions for the economy, premium, and low-cost passengers, respectively.	Latent Semantic Analysis	TripAdvisor	N/A	MathLab	5 120 reviews
(Lucini et al., 2020)	Passenger nationality and type of cabin flown influence satisfaction. Type of traveler had minimal impact.	Latent Dirichlet Analysis/Sentiment Analysis (Naïve Bayes Classifier)	Skytrax	Python programmed	N/A	55 775 reviews

(Song et al., 2020)	Investigated how delays affect passenger sentiment; There is a negative correlation between passenger sentiment and flight delay.	Topic modeling/Sentiment Analysis (Lexicon-based)	Skytrax	Python’s Requests library	VADER - Valence Aware Dictionary and Sentiment Reasoner	24 165 reviews
(Zhang et al., 2016)	Analyzed six North American airlines; Developed an approach that can provide recommendations for potential passengers to recommend the airline that best matches the passengers’ demands.	Topic modeling/Sentiment Analysis (Dictionary-based)	Twitter	Tweepy (python)	VADER – Valence Aware Dictionary and Sentiment Reasoner	14 560 comments
(Xu et al., 2019)	Studied the impact of service failure and recovery attempts on airline passengers’ satisfaction and emotions; Found out that providing compensation for the current trip can ease passengers’ negative emotions. Passengers’ emotions influence their satisfaction, as well as the likelihood of recommending the airline.	Topic modeling/Sentiment Analysis	Skytrax	WebHarvy	SentiStrength	2 439 reviews
(Khan & Urolagin, 2018)	Research about customer loyalty; Proposed a system that analyses and predicts customer loyalty	Random Forest, Decision Tree	Twitter	Tweepy (python)	TextBlob (python)	10 000 comments

(Sternberg et al., 2018)	Investigation to whether business data can be estimated through analyzing airline Facebook page; It concluded that it is not possible to predict such data, but it is possible to estimate customer satisfaction.	Text classification (Naïve Bayes Classifier); Keyword analysis	Facebook	SODATO	Mutato	5 488 066 data points
(Heidari & Rafatirad, 2020)	Implements a Convolutional Neural Network model that can recommend airline tickets.	Sentiment Analysis	Google Flights, Kayak, Skyscanner, Twitter, Hotels.com, TripAdvisor	Retrieved through the API of each platform	Bidirectional Encoder Representations from Transformers (BERT) / TextBlob (python) / TF-IDF	3.5 million comments
(Lacic et al., 2016)	Research of which factor contributed the most to passenger satisfaction and if it is possible to predict said satisfaction; Found out that sentiment has a correlation with satisfaction and that it is possible to predict passenger satisfaction.	Topic modeling (Suffix Tree Clustering)/ Sentiment Analysis	Skytrax	Publicly available dataset	AlchemyAPI	62 639 reviews
(Dhini & Kusumaningrum, 2019)	The study obtains aspects and sentiment classification of Soekarno-Hatta Airport's customer reviews to provide airport management with the most complained aspects to achieve customer satisfaction.	Topic Modeling (Naïve Bayes Classifier/Support vector machine)	Google Review	Agenty	Statistica 10	7 813 reviews

(Michailidis et al., 2018)	Developed a sentiment analysis tool that allows airlines to measure their passengers' satisfaction. The tool can download and classify tweets, displaying the results in interactive maps.	Sentiment Analysis (Support Vector Machine)	Twitter	CrowdFlower	AirSent	15 000 comments

All in all, it is possible to conclude that different passengers from distinct airlines, traveling in different cabins, having different nationalities leads to different expectations and levels of satisfaction. Comfort, flight disruptions, staff friendliness, and value are the factors that most affect satisfaction in passengers, at least before the pandemic. It is also noteworthy that some studies linked loyalty to satisfaction. Naïve Bayes algorithm seems to be popular in these studies, although some have come across better-performing algorithms. Regarding the data source, the review website Skytrax seems to be the most used, Twitter being the runner-up.

2.3. IR2

2.3.1. Review protocol

The same libraries, filters and inclusion and exclusion criteria were used for IR2. Only the search string changed to "Airline AND Satisfaction AND (Mining OR Sentiment) AND covid". Only articles from 2020 to 2021 were considered since these years correspond from the beginning of the COVID-19 pandemic to the present day (Albers & Rundshagen, 2020). The articles were searched between January 6th, 2021 and January 7th, 2021.

2.3.2. Conducting the review

Table 5 shows the obtained documents for IR2, as well the databases, keywords and filter that were used.

Table 5 - *Documents obtained based on filter application*

DB	Keywords	F1 - Full Text	F2 - Only Abstract	F3 - Duplicates Removal
IEEE Xplore	Airline AND Satisfaction AND Mining AND COVID	0	0	0
	Airline AND Satisfaction AND Sentiment AND COVID	0	0	0
Web of Science	Airline AND Satisfaction AND Mining AND COVID	0	0	0
	Airline AND Satisfaction AND Sentiment AND COVID	0	0	0
EBSCO	Airline AND Satisfaction AND Mining AND COVID	15	0	0
	Airline AND Satisfaction AND Sentiment AND COVID	10	0	0
	Total	**25**	**0**	**0**

After we gathered this set of papers, the content relevance was assessed for this review (exclusion criteria) and, only then, the final set of papers was obtained.

2.3.3. Report

Only 15 papers were found in the search. Of those 15, only one comes close to the topic studied in this dissertation. The article by Monmousseau et al. (2020) studies how passengers reacted on Twitter after lockdown events. The mood (sentiment) was assessed on those comments. The study concluded that airlines reacted differently to travel restrictions. The study was able to determine, based on the keyword “canceled” and “refund”, which airlines had the best refund policy. This information could help future passengers to choose the airline that best suit their needs. However, the study appears to be somewhat limited since it did not explore if those cancelations and refunds affected passenger satisfaction (because Twitter is not a review website). It also did not compare with the previous level of satisfaction (pre-COVID-19 period).

2.4. Airline passenger satisfaction

One output that results from the purchase of a product or the use of a service is satisfaction. It develops from the contrast between benefits, cost, and expectations (Sezgen et al., 2019). Customer satisfaction can be measured by the cumulation of satisfaction originating from products/services (Churchill & Surprenant, 1982).

In the literature, it has been widely accepted the approach to customer satisfaction by Oliver (1980) who defines it as a function of expectation and expectancy disconfirmation. The theory says that consumers develop an expectation about a specific product or service, before its purchase, that will be seen as the standard to said product/service. Once the customer uses the product/service, it will compare the experience with the pre-purchase expectations. Three scenarios may emerge: if the perceived performance matches the expectation, the customer is satisfied. If the expectations are exceeded, the customer is also satisfied. However, dissatisfaction might occur if the expectations are not met (Yüksel & Yüksel, 2001). For an airline passenger, when the service quality attributes that the passenger values the most are met or exceled, the passenger tends to be satisfied (Chow, 2015). Those attributes depict the various dimensions of satisfaction (Guo et al., 2017).

The airline industry, by nature, is very dynamic, so it is not easy to distinguish airlines from one another and describing each one of them in a uniform way (Mason & Morrison, 2008). However, Zeithaml (1988) explains that from the perspective of the passengers, expectations and perceptions of an airline service may differ according to the different business models between a low-cost and a full-service airline.

Zeithaml (1988) adds that it would be reasonable to expect that passengers from low-cost airlines have different expectations from passengers traveling with a full-service airline. In fact, in a study carried by Forgas et al. (2010) it was concluded that low-cost passengers' satisfaction is mainly influenced by monetary cost and service quality. For full-service airline passengers, on the other side, it was the professionalism of the cabin crew that was essential for the passengers' satisfaction.

Zeithaml (1988) also mentions that even passengers from the same airlines might form different expectations between them. For example, passengers flying in a premium cabin as opposed to those flying in economy. This could be explained since the consumer utility expectations increase proportionally to the amount paid (Zeithaml, 1988). On a study conducted by Lucini et al. (2020), it was found that passengers traveling in different classes had indeed different expectations. In the study it was found that customer service was paramount to passengers traveling in First Class. Economy Class passengers, on the other side, gave more importance to prices in airports, waiting times, checking luggage, and delays. It was also possible to find similarities among different nationalities. For example, it was concluded Americans and Canadians seem to exhibit the same behavior when writing about satisfaction dimensions which, in turn, contrasts with the writing of the British and Australians. Finally, the type of passenger (e.g. solo traveler) had a minimal impact on the customer satisfaction dimensions (Lucini et al., 2020).

Many studies concluded that customer satisfaction can ultimately affect customers' loyalty, if they are satisfied that will translate into positive reviews, product recommendations, and returning customers (Forgas et al., 2010; Guo et al., 2017; Mattila, 2004). If not, however, in the case of airlines that might result in passengers reconsidering using the same airline in the future (Namukasa, 2013), and even negative word of mouth that can cause damage to the airline's reputation (Blodgett & Li, 2007).

Zhang et al. (2016), on a study in which 14560 comments were collected from Twitter from six North American airlines, concluded that airlines have predominantly positive reviews or predominantly negative reviews. Meaning that passengers tend to praise or complain about an experience rather than writing a neutral comment.

The question that remains is what dimensions influence satisfaction on airline passengers. Table 6 tries to answer that question by summarizing articles that extracted some satisfaction dimensions expressed by the passengers, and some were able to assess if a particular dimension affected the passenger's satisfaction using linear regression. At first sight it appears that mostly every factor will influence a passenger's satisfaction, the only dimension that appears not to influence satisfaction is the procedure of checking luggage at the airport. However, it is known that passengers give more importance to certain dimensions than others (Lucini et al., 2020).

Table 6 - *Satisfaction dimensions and their influence on passengers*

Satisfaction Dimensions	Influences satisfaction/sentiment	Literature
Friendliness and helpfulness of staff/Customer Service	✔	Sezgen et al. (2019); Lucini et al. (2020); Song et al. (2020); Lacic et al. (2016)
Hassle-free customer experience	✔	Sezgen et al. (2019); Lucini et al. (2020)
Comfort of the seat	✔	Sezgen et al. (2019); Lucini et al. (2020); Song et al. (2020); Zhang et al. (2016); Lacic et al. (2016)
Value	✔	Sezgen et al. (2019); Lucini et al. (2020); Song et al. (2020); Zhang et al. (2016); Lacic et al. (2016)
Food and Beverage	✔	Sezgen et al. (2019); Lucini et al. (2020); Song et al. (2020); Zhang et al. (2016); Lacic et al. (2016)
In-flight service	✔	Sezgen et al. (2019); Lucini et al. (2020); Song et al. (2020); Zhang et al. (2016); Lacic et al. (2016)
Airplane characteristics	✔	Lucini et al. (2020); Lacic et al. (2016)
Airport Lounge	✔	Lucini et al. (2020); Lacic et al. (2016)
Delays	✔	Lucini et al. (2020)
Terminal infra-structure	✔	Lucini et al. (2020); Song et al. (2020); Lacic et al. (2016)
Check-in procedures	✔	Lucini et al. (2020)
Checking luggage	✖	Lucini et al. (2020)
Cabin flown	N/A	Zhang et al. (2016)
Wi-Fi & Connectivity	✔	Zhang et al. (2016); Lacic et al. (2016)
Ground Service	N/A	Zhang et al. (2016)
Route	N/A	Zhang et al. (2016)
In-flight Entertainment	N/A	Zhang et al. (2016); Lacic et al. (2016)

Moreover, a study carried by Lacic et al. (2016) tried to understand which satisfaction dimensions influence airline passengers the most and to what extent that satisfaction can be predicted. The authors used a pre-made dataset from Skytrax and explored four different review categories: airport, lounge, airline, and seat reviews. A feature analysis was performed in which the review rating was correlated to the overall sentiment. It was concluded that queuing time, lounge comfort, cabin crew quality, and seat legroom were the features that had the most impact on passenger satisfaction. They also found out that sentiment is a good indicator (strong correlation) to whether the passenger was satisfied or not (Lacic et al., 2016).

Regarding service failure and disruptions, in a study carried by Song et al. (2020), it was concluded that flight delays affect passengers' sentiment negatively. The study adds that it can be inferred that passengers are not satisfied with the compensation mechanisms offered by airlines following flight delays and that the passengers' attention to service aspects tends to increase after the disruption of service. In contrast, Xu et al. (2019) found out that passenger compensation following service disruption positively affects the customer's emotions. However, if the compensation is for a future trip, it does not influence the emotion positively, even if it is monetary compensation. Airlines are advised to provide either monetary or non-monetary compensations (e.g., upgrades, priority boarding, or complimentary meals) for the current trip to ease the passengers' frustrations. Xu et al. (2019) also found out that employee attitude towards dissatisfied or complaining passengers also affects the passengers' emotions. Service failure also has more impact on full-service airline passengers than those traveling on low-cost airlines. This is explained by the higher fare that full-service passengers pay, which in turn, comes with higher expectations. For the same reason, the type of cabin flown also impacts the emotions regarding service failure. Business-class passengers that pay higher airfares are more affected than economy passengers. Finally, it is also known that positive emotions raise the passenger's satisfaction level and that negative emotions lower those levels. (Xu et al., 2019).

Chapter 3 – Methodology

3.1. Population and sample

In 2020, Skytrax performed the world's only assessment and certification of the health and safety measures taken by the airlines during the pandemic. Each airline is being submitted to a professional and scientific investigation of the standards provided to passengers at the airport and onboard the aircraft. Afterward, airlines are awarded a final rating (that goes from one to five stars), five stars meaning that the airline implemented strict safety protocols that enhance passengers and staff safety, and one star meaning the opposite (Skytrax, 2021b).

For this study, the intended population are all passengers who have flown with an airline at least one time. The sample consists of a dataset with 9,743 reviews published in Airlinequality.com. The selected airlines where those which had an attributed COVID-19 rating (Table 7). Airlinequality.com is the top review site for airlines, airports, and associated air travel reviews (Skytrax, 2021a). It is owned by Skytrax, a brand that is recognizable for its Airline and Airport Star Rating, the World Airline Awards, and Airport Awards (Skytrax, 2021a). Airlinequality.com prides itself on being an independent customer forum, with no financial association with any of the airlines or airports featured (Skytrax, 2021a).

Table 7 - *Selected airlines and respective COVID-19 rating on Skytrax*

Airline	COVID-19 Rating
Aegean Airlines	4
Air France	4
airBaltic	5
AnadoluJet	3
Blue Air	3
British Airways	4
easyJet	4
Iberia	4
KLM Royal Dutch Airlines	4
LOT Polish	3
Lufthansa	4
Pegasus Airlines	3
Ryanair	4
Turkish Airlines	4
Vueling	4
Wizz Air	3

3.2.Data collection

We resorted to a web scraper to collect all the existing reviews efficiently and effectively from the selected airlines available on airlinequality.com. A web scraper is a tool or a piece of code that can be used to extract specific data from web pages. This technique, for example, is used by search engines as a way to compile information about the many existing websites on the Internet (Octoparse.com, 2021). For this task, Octoparse.com, a well-known web scraping tool, was used to collect the reviews and used in previous studies (Hamada & Naizabayeva, 2020).

Each collected review had several fields with all the relevant information available on the website, which might enrich this study's findings. Table 8 depicts the fields available for each observation on the dataset, as well a small explanation of said field.

Table 8 - *Data on each observation of the dataset*

Review	
Airline_Name	Airline flown by the reviewer
Rating	Rating given by the reviewer, on a scale from 1 to 10, being 10 the best and 1 the worst
Text	Text of the review
Country	Country from which the reviewer originates from
Class	Class of travel, being the possible values “First Class”, “Business Class”, “Premium Economy” and “Economy Class”
Travel_Date	Date of the flight, on a DD/MM/YYYY format
Recommend	Boolean (YES/NO) indicating if the reviewer recommends the airline flown.
ID	Unique identifier of the review

A total of 16,583 reviews were collected. However, reviews prior to 2016 did not have consistent data. Some fields had missing values, and for that reason, they were discarded. The final number of reviews in the dataset is 9,743, dating from January 2016 until February 2021.

3.3. Data analysis

Text Mining is a data mining technique where structured and unstructured data is processed and analyzed (Ramos et al., 2019). More recently, with the increasing amount of text data that is being generated on websites, social media, and news, more studies about text mining have been conducted. In this study, we will be recurring mainly to sentiment analysis for analyzing the gathered data.

As opposed to text mining, which deals with the recognition of prevailing facts within a given text, sentiment analysis identifies the sentiment that lies within a subjective statement or opinion and can be either classified as positive, negative, or neutral (Rout et al., 2018). Sentiment analysis is defined by Nasukawa and Yi (2003) as an analytic method of big data that identifies the polarity of sentiment in expressions or judgments made by the consumers. Xiang et al. (2017) add to the definition saying that sentiment analysis is a technique that results from artificial intelligence, natural language processing, information extraction, and information retrieval.

There are four types of approaches: dictionary-based, machine learning, statistical, and semantic (Tsytsarau & Palpanas, 2012). As the tool used in this study relies upon the dictionary-based method, we will focus on that approach. A dictionary-based technique generally relies on a dictionary containing words and phrases that have attributed scores ranging from +1 (strongly positive) to -1 (strongly negative) (Lexalytics.com, 2020). When calculating the sentiment for a specific document, the content of that document is evaluated to see if there is a match with the words in the dictionary. The polarity of a document will result from the sum of polarities of the individual words or phrases (Devika et al., 2016). Sometimes the weight of a certain word must be adjusted because of the modifier that accompanies it (Lexalytics.com, 2020). Negators (for example, never or not) and intensifiers (for example, much and very), are the most common modifiers. A negator usually reverses the word's score in the dictionary, while an intensifier might raise the score or even sometimes lower it.

We used Semantria to calculate the sentiment in the text. Semantria is a text and sentiment analyzing tool developed by Lexalytics (Lexalytics.com, 2021b). This tool has an "industry pack" for the aviation industry. In other words, Semantria contains an industry-specific dictionary. An "industry pack" calibrates the sentiment engine to be more accurate to a specific subject (in this case, the aviation industry), meaning that the sentiment score will be much more precise, contributing to more accurate results (Lexalytics.com, 2021a).

Each score represents the polarity of the sentiment that is present in a text. The polarity in Semantria ranges from -2 to 2 and Table 9 describes the default classification scheme set by Semantria, which was used in this study.

Table 9 - *Sentiment classification according to polarity score*

Sentiment polarity range	Classification
[-2, -0.05[	Negative
[-0.05, 0.22[	Neutral
[0.22, 2]	Positive

At this point, it is important to define when the COVID-19 period begins. For this matter, it was reported that European airlines began reacting to the COVID-19 pandemic as early as January 2020 (Albers & Rundshagen, 2020). European carriers also saw the first COVID-19-related flight cancelations in late January (IATA.org, 2020). In light of the aforementioned facts, January appears to be the initial period in which passengers felt for the first time the COVID-19 restriction. For that reason, in this study, January 2020 will be considered the beginning of the COVID-19 period.

Finally, in preparation for the sentiment analysis, the dataset was divided into two independent samples, covering two time intervals, one corresponding to the pre-COVID-19 period (before January 2020) and the other corresponding to the post-COVID-19 period (after January 2020). These datasets were then analyzed using Semantria in the Microsoft Excel. The results will be presented in the next chapter.

Chapter 4 – Results and discussion

We will start by characterizing the sample. Tables 10 and 11 describe the distribution of the passengers by class and country, respectively, for both the pre-COVID-19 and the COVID-19 period.

Table 10 - *Passengers by class, pre-COVID-19*

Travel Class	Pre-COVID-19		COVID-19	
	Absolute frequency	Relative frequency	Absolute frequency	Relative frequency
Business Class	1372	15,48%	100	11,35%
Economy Class	6959	78,53%	754	85,58%
First Class	154	1,74%	7	0,79%
Premium Economy	377	4,25%	20	2,27%
Total	**8862**	**100,00%**	**881**	**100,00%**

Table 11 - *Top 20 countries of the sample*

Country of origin	Pre-COVID-19		Country of origin	COVID-19	
	Absolute frequency	Relative frequency		Absolute frequency	Relative frequency
United Kingdom	3191	36,01%	**United Kingdom**	248	28,15%
United States	1104	12,46%	**United States**	124	14,07%
Germany	500	5,64%	**Germany**	53	6,02%
Canada	359	4,05%	**Canada**	37	4,20%
Netherlands	310	3,50%	**Netherlands**	30	3,41%
Australia	245	2,76%	**Spain**	28	3,18%
France	217	2,45%	**France**	26	2,95%
Greece	183	2,06%	**Ireland**	24	2,72%
Spain	182	2,05%	**Portugal**	23	2,61%
Switzerland	176	1,99%	**Australia**	17	1,93%
Ireland	157	1,77%	**Greece**	17	1,93%
Italy	151	1,70%	**Switzerland**	16	1,82%
Poland	116	1,31%	**Italy**	16	1,82%
Portugal	96	1,08%	**Poland**	15	1,70%
Belgium	94	1,06%	**Czech Republic**	13	1,48%
Turkey	94	1,06%	**Sweden**	11	1,25%
Singapore	90	1,02%	**Norway**	9	1,02%
Sweden	82	0,93%	**Singapore**	9	1,02%
Romania	74	0,84%	**Russian Federation**	9	1,02%
Czech Republic	74	0,84%	**Turkey**	9	1,02%
Others	1367	15,43%	**Others**	147	16,69%
Total	**8862**	**100,00%**	**Total**	**881**	**100,00%**

It is apparent that most passengers wrote review travels in economy class in both periods (78,53% and 85,58%, respectively) and are from the United Kingdom (36,01% and 28,15%, respectively).

Semantria calculated the sentiment polarity for each review. In addition, as mentioned before (Table 8), we also collected other relevant information regarding each review. Figure 3 demonstrates, during the pre-COVID-19 period, the distribution of the reviews regarding the polarity attributed to each one (Positive, Negative or Neutral), as well the rating given by the passengers (ranging from 1 to 10) and if it recommends the airline (Yes or No).

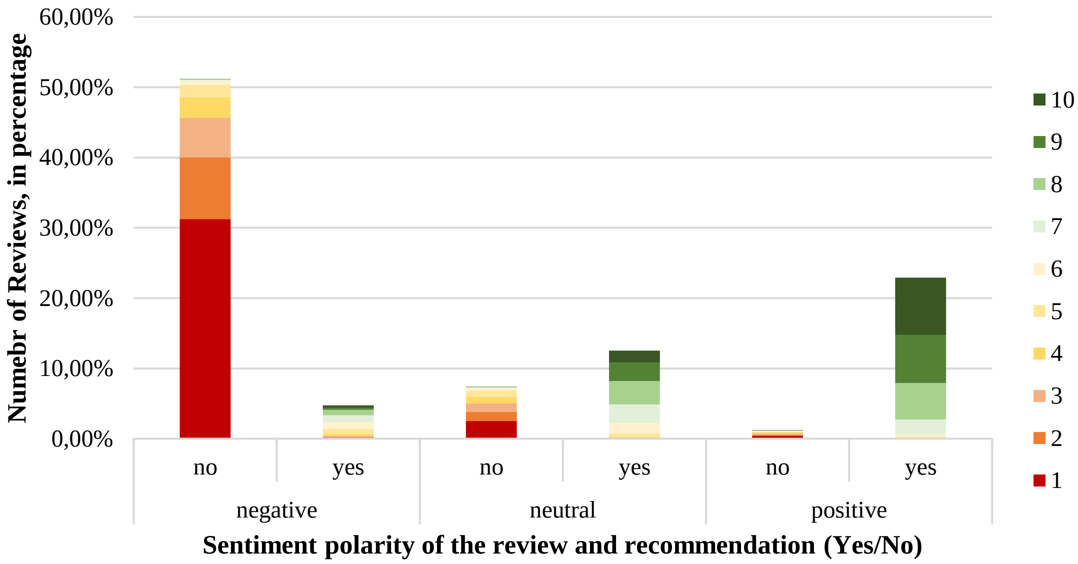

Fig. 3 - *Review rating and sentiment polarity distribution, pre-COVID-19 period*

Immediately, it is possible to acknowledge that most of the reviews classified with negative polarity are the ones with the lower rating and with a negative recommendation (NO). Similarly, most of the positive reviews exhibit higher ratings and positive recommendations (YES). As expected, passengers who positively recommend the airline are more likely to leave a positive review with a high rating. The opposite also happens, confirming the findings of Xu et al. (2019) in which is mentioned that positive emotions increase satisfaction levels, and negative emotions decrease satisfaction.

From the pre-COVID-19 dataset, 24.18% of the reviews were classified as positive, 19.92% as neutral, and a whopping 55.90% as negative. This means that more than half of the reviews present on Skytrax from January 2016 to December 2019 are most likely complaints or dissatisfaction with the airline's service. It is also worth mentioning that according the expectancy-disconfirmation theory formulated by Oliver (1980), passengers recommending the airline must have had their expectations met, otherwise they do not recommend an airline. The results show that most passengers are not having their expectations met.

We can also recognize that the ratings **7**, **8**, **9,** and **10** explain 22.46% of the 24.18% population of positive reviews classified by Semantria. In the same way, ratings **1**, **2**, **3,** and **4** explain 49.25% of the 55.90% population with reviews classified as negative. This indicates that the Semantria algorithm accurately identifies sentiment since the results are more or less in line with the rating classification system created by the passengers. Finally, the fact that the reviews are predominantly negative (55.90%) can be explained since people have the tendency to complain or praise about an experience rather than leaving a neutral review as mentioned by Zhang et al. (2016), which also explains why neutral ratings such as **5** and **6** rarely occur in the sample.

Figure 4 illustrates the same data mentioned above but during the COVID-19 period.

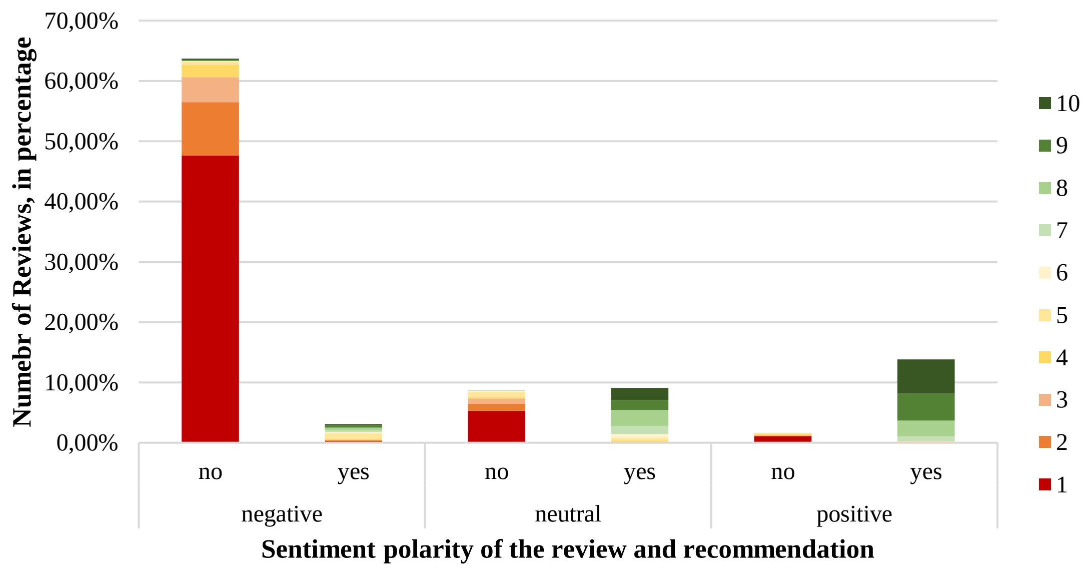

Fig. 4 - *Review rating and sentiment polarity distribution, COVID-19 period*

The overall distribution appears to be similar to the distribution exhibited in the pre-COVID-19 period. However, it is quite apparent that the number of negative reviews has increased, suggesting that the COVID-19 restrictions worsened the travel experience. In this dataset, 15.45% are positive reviews, 17.81% are neutral and 66.75% are negative.

Unlike the previous dataset, here most of the neutral reviews appear to have a rating of **1**, further emphasizing the overall negative attitude towards the airline industry.

Lastly, the passengers' ratings appear to be condensed on the extremities of the rating scale. Rating **1** explains 47.88% of the population of 66.75% negative reviews, and ratings **9** and **10** explain 10.14% of the population of 15.45% positive reviews. These results further emphasize the findings of Zhang et al. (2016) in which is stated that people rather praise or complain about an experience, than leaving a neutral review.

Semantria, thanks to the built-in topic detection function, can also classify each sentence of the reviews into airline industry-related categories. Figures 5 and 6 illustrate the ten most mentioned airline-related categories during the pre-COVID-19 period for Low-Cost Carrier (LCC) and Full Service Carrier (FSC) respectively. It is possible to know how many positive, neutral, and negative mentions for each category. The description of each mentioned category can be seen in Appendix I.

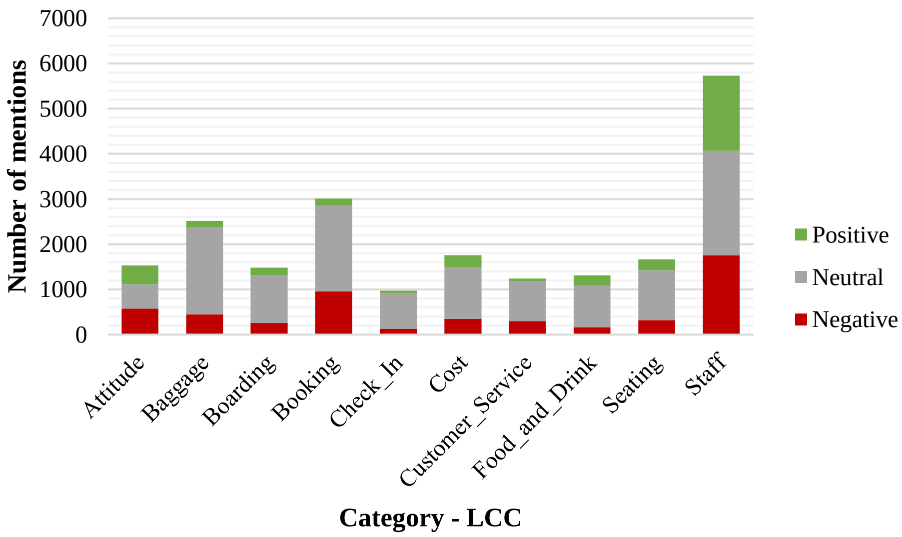

Fig. 5 - *Number of mentions, by category for LCCs during the pre-COVID-19 period*

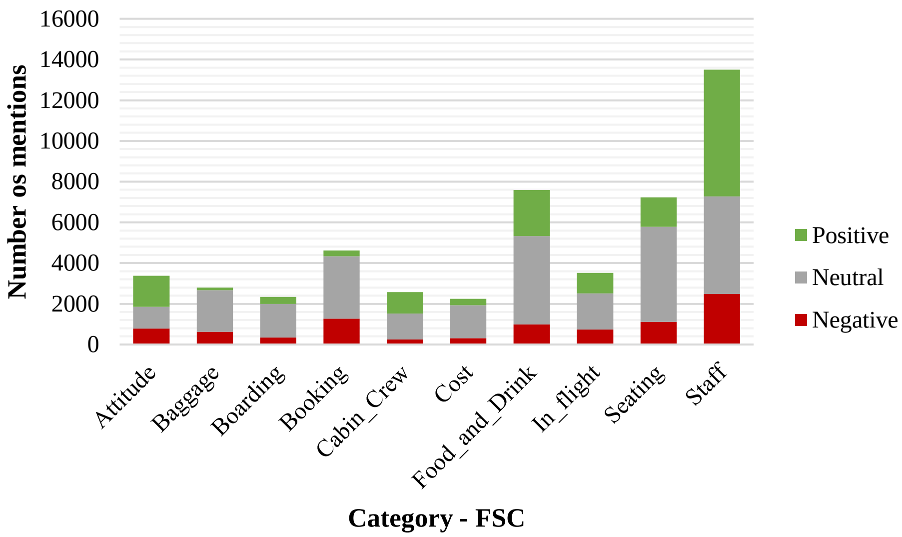

Fig. 6 - *Number of mentions, by category for FSCs during the pre-COVID-19 period*

It becomes apparent that **Staff** is the most mentioned aspect by both the LCC and FSC passengers. This indicates that passengers give attention to how they are treated by the airport staff and cabin crew and if they are helpful or not. This should not come as a surprise since several studies mentioned that the airport staff and cabin crew are some of the factors that most influence passenger satisfaction, and in turn, sentiment, as depicted on Table 6 (e.g., Lacic et al., 2016; Lucini et al., 2020; Sezgen et al., 2019; Song et al., 2020). Sezgen et al. (2019) goes as far as saying that staff attitude is one of the most important satisfaction and dissatisfaction attribute for all passenger groups. In other words, passenger satisfaction varies proportionally with the performance of this attribute.

Seating, **Food_and_Drink, Baggage** and **Booking** appear to be important factors that also influence passenger satisfaction since these are the most mentioned. It is also noteworthy that most of the dimensions of satisfaction identified in Figures 5 and 6 were also identified in other studies, as shown in Table 6.

Figures 7 and 8 show the mean sentiment polarity for each category for LCCs and FSCs respectively, for the same period. The colors of the bars represent the sentiment polarity, red for negative (score under -0.05), grey is for neutral (between -0.05 and 0.22), and green is for positive (above 0.22).

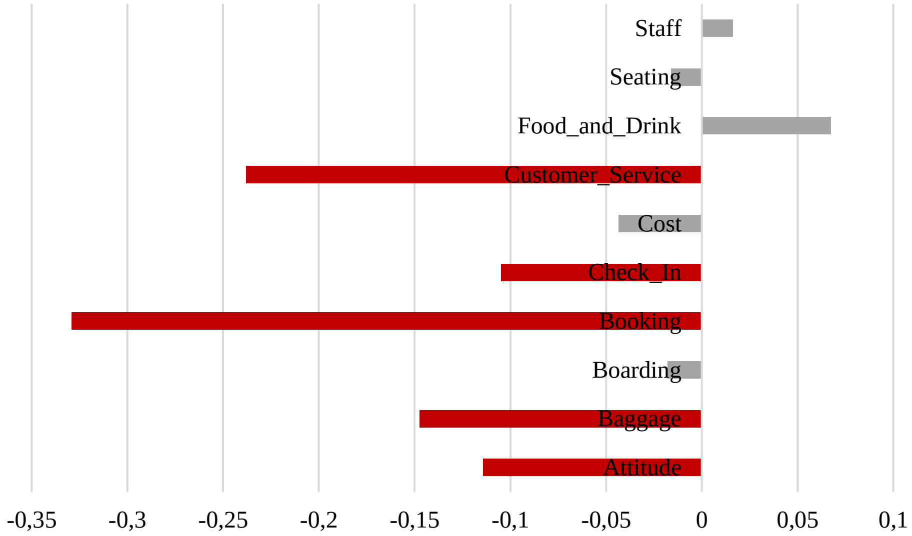

Fig. 7 - *Mean sentiment polarity, by category for LCCs, during the pre-COVID-19 period*

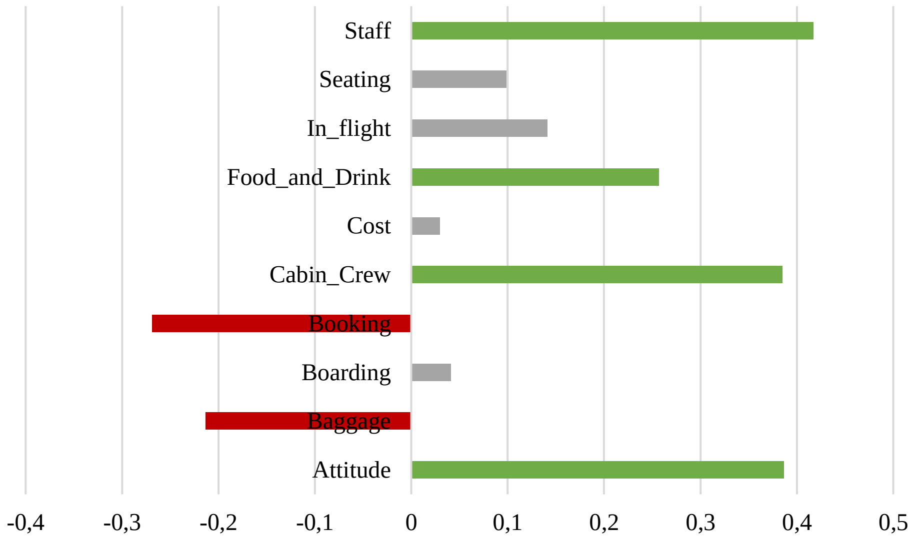

Fig. 8 - *Mean sentiment polarity, by category for FSCs, during the pre-COVID-19 period*

It is evident that LCC passengers have mostly negative experiences across most of the satisfaction dimensions while, in contrast, FSC passengers have mixed experiences but mostly positive ones. More or less the same dimensions are mentioned between LCCs and FSCs. The only differences are that LCC passengers mention negative experiences with **Customer_Service** and **Check-In**, while FSC passengers mention a positive experience with **Cabin_Crew** and a neutral experience with **In_Flight** aspects.

These findings are close to the findings of Forgas et al. (2010) in which FSC passengers value more the professionalism of the personnel and LCC passengers value more the quality of service, justifying why dimensions such as **Cabin_Crew** appear only in the sample containing reviews of FSCs and **Customer_Service** in the sample containing LCCs. Lastly, **Booking** and **Baggage** are the aspects that contribute to a negative experience in both LCCs and FSCs, suggesting that these aspects are to be improved by the airlines.

Researchers have explored the possibility that the type of cabin flown may also influence passenger satisfaction and sentiment differently (Lucini et al., 2020; Sezgen et al., 2019). In fact, Economy class and Premium Economy passengers (see appendix A and B) demonstrate having mostly positive polarity towards **Cabin_Crew-Attitude** and **Staff-Helpfulness**, which is in line with the findings of Sezgen et al. (2019) in which Economy cabin passengers value *Friendly-helpful staff* and *Hassle-free customer experience*. These types of passengers also appear, by the number of mentions, to give importance to **Cost**, specifically **Baggage_Cost** (luggage fees, for example) and **Food_and_Drink-Cost**. These results means cost-conscious passengers that are only interested in getting from point A to point B, confirming the findings of Lucini et al. (2020). Regarding Business and First Class passengers (see appendix C and D) they also seem to praise **Cabin_Crew-Attitude** and **Staff-Helpfulness** but do not exhibit a significant number of mentions for **Cost**, which is also in line with the finding of Licini et al. (2020) that states that customer service is paramount to passengers traveling in First Class. They focus on **Seating_Quality**, **In-flight_Quality, Lounge,** and **Food_and_Drink-Quality**, appearing to be a type of passenger that appreciates the value of the product that the airlines offer.

Lastly, Table 12 shows that First Class passengers are the most satisfied and with higher sentiment polarity, followed by Business, Premium Economy, and Economy Class. The average rating appears to corroborate the sentiment polarity, which is to be expected as Lacic et al. (2016) found that the review rating is correlated to the overall sentiment.

Table 12 - *Average rating and sentiment polarity, by travel class, pre-COVID-19*

Travel Class	Average rating	Average sentiment polarity
Business Class	5,71	0,049
Economy Class	4,18	-0,102
First Class	6,26	0,137
Premium Economy	4,84	-0,009
Total	**4,47**	**-0,071**

Regarding the COVID-19 period, Figures 9 and 10 illustrate the ten most mentioned satisfaction dimensions, for Low-Cost Carrier (LCC) and Full Service Carrier (FSC) respectively.

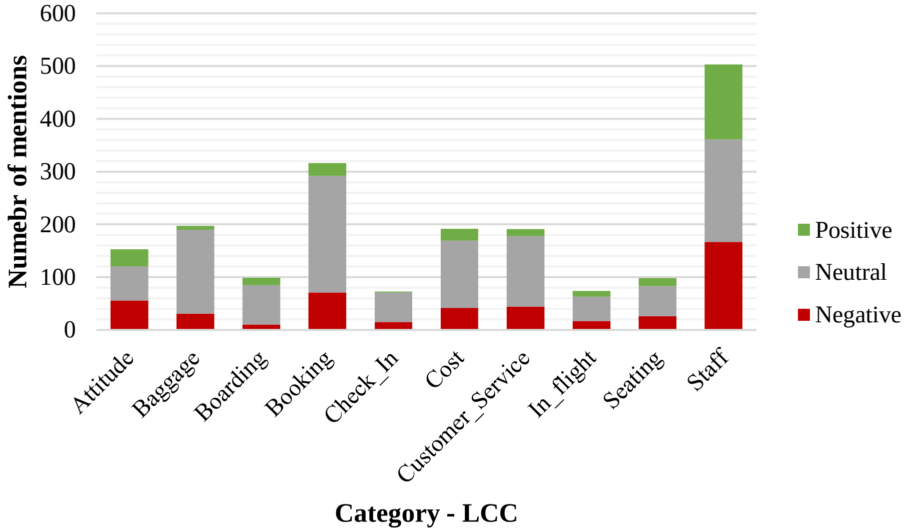

Fig. 9 - *Number of mentions, by category for LCCs during the COVID-19 period*

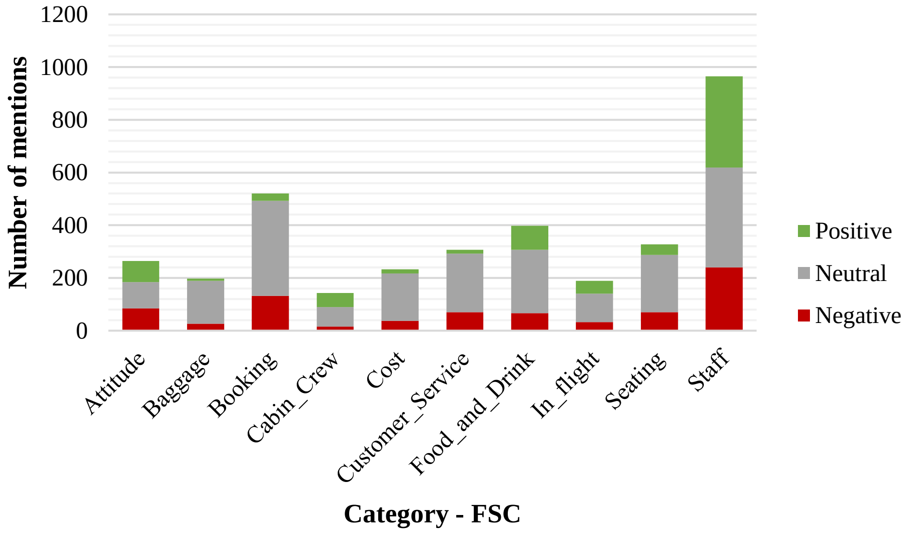

Fig. 10 - *Number of mentions, by category for FSCs during the COVID-19 period*

By comparison with the pre-COVID-19 period there are not that many changes. **Staff** remains the central aspect that passengers talk about. Mentions about **Booking** appear to have increased for FSC passengers, as well **Customer_Service**, which previously did not make the top ten categories of FSC passengers. Regarding LCC passengers, the only difference is that the category **Food_and_Drink** disappeared from the top ten, giving its place to **In_Flight**. This is to be expected since it is known that due to COVID-19 restrictions, airlines reduced, and some even completely suspended, the onboard food service (Foodandwine.com, 2020).

Figures 11 and 12 show the mean sentiment polarity for each category for LCCs and FSCs respectively, during the COVID-19 period.

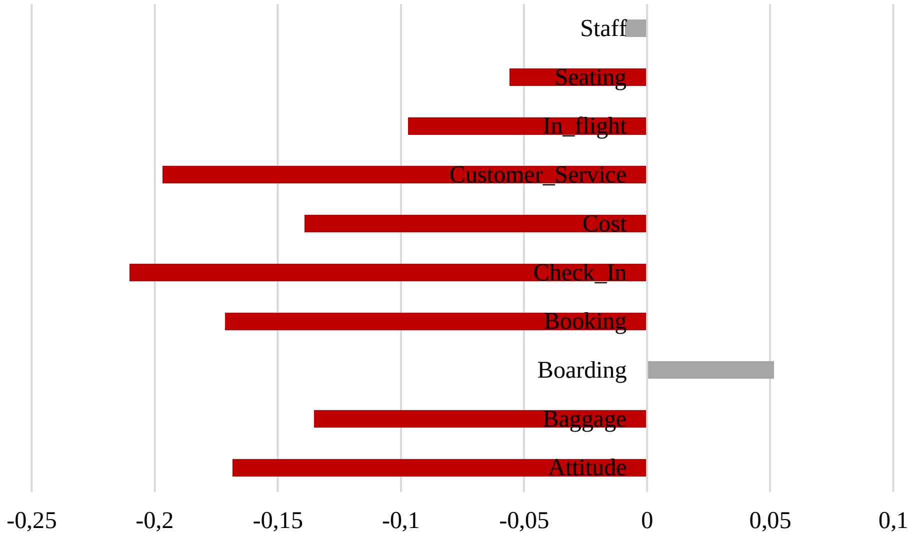

Fig. 11 - *Mean sentiment polarity, by category for LCCs, during the COVID-19 period*

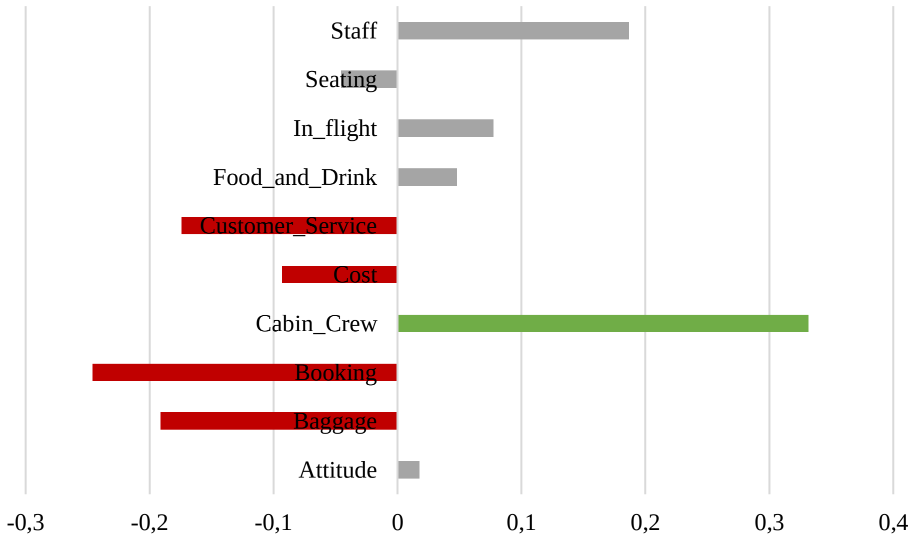

Fig. 12 - *Mean sentiment polarity, by category for FSCs, during the COVID-19 period*

Similarly, to the pre-COVID-19 period, it is evident that LCC passengers have a mostly negative sentiment towards most of the categories. There are no categories with a positive sentiment. When compared to the pre-COVID-19 period the categories **Seating** and **Cost** became negative. As mentioned by Forgas et al. (2010) LCC passengers are sensitive to monetary cost and, due to the pandemic, airfares have actually increased (Barrons.com, 2020), explaining the decrease in the sentiment polarity of **Cost**. The negative sentiment in **Seating** might be explained due to some airlines occupying the middle seats with passengers, disregarding the guidelines of social distancing (Nytimes.com, 2020).

Regarding the FSC passengers, the categories **Staff**, **Attitude and Food_and_Drink** became neutral. As FSC passengers value the professionalism of airline employees, the protocols in place to contain the pandemic might have impacted the way that the employees perform their job, resulting in a worse sentiment towards this specific aspect. Regarding the **Food_and_Drink** sentiment decrease, it can be easily explained since, as mentioned before, some airlines reduced or even suspended the food offerings onboard (Foodandwine.com, 2020) Finally, **Cost** became negative, understandably for the same reason mentioned above that states that the airfares have risen (Barrons.com, 2020).

The only positive sentiment is towards **Cabin_Crew,** remained more or less the same. This is to be expected since during the pandemic cabin crew functions remained the same in-flight, at least in the passenger's perspective. They still greet and serve the passengers, while ensuring the passengers' safety.

Overall, the factors that influence the satisfaction of the passengers have not changed during the COVID-19 period. However, it is noticeable a surge of mentions in **Customer_service-refunds** and **In_flight-Cabin-Cleanliness** in Economy Class passengers, as well in Business Class passengers (see appendix E and G).

The surge of **Customer_service-refunds**, as mentioned by Dada (2021), can be explained because airlines have been known to intentionally hinder the refund process, making passengers wait long periods and, to an extreme, not answering the passenger's contact attempts. Some airlines are processing refunds through vouchers that the passenger can redeem at a later date. However, despite the financial stress that airlines worldwide are going through, they are obligated to refund the passenger. These situations are causing passengers to go on social media to complain (Dada et al., 2021).

Regarding **In_flight-Cabin-Cleanliness**, it can be explained simply because due to the corona virus. Passengers nowadays pay more attention to infection prevention and disease control procedures in order to feel safe (Sotomayor-Castillo et al., 2021).

According to Table 13, overall, the rating and sentiment have worsened during the COVID-19 period for all travel classes except First Class. The average rating of First Class passengers has increased, however the sentiment polarity did not.

Table 13 - *Average rating and sentiment polarity, by travel class, COVID-19 period*

Class	Average rating	Average sentiment polarity
Business Class	4,62	-0,037
Economy Class	3,06	-0,183
First Class	7	0,098
Premium Economy	4	-0,041
Total	**3,29**	**-0,162**

Finally, Table 14 allows us to compare the Skytrax COVID-19 ranking with the passengers' cleanliness scores.

Table 14 - *Average cleanliness ranking vs. Skytrax COVID-19 ranking, by airline*

Airline Name	Average Rating	Skytrax COVID-19 Rating
airBaltic	10	5
Vueling Airlines	9	4
Wizz Air	8,67	3
easyJet	8,4	4
Aegean Airlines	8	4
Lufthansa	7,6	4
British Airways	7,1	4
Ryanair	7	3
KLM Royal Dutch Airlines	5,75	4
LOT Polish Airlines	5,5	3
Air France	5	4
Turkish Airlines	4,67	4

It is worth mentioning that this average rating only contributed to reviews that focused on in-flight cleanliness (cabin and bathroom), airport lounge cleanliness, and airport boarding area cleanliness. Although this method might not be the most accurate, it reveals that at least for Air Baltic, their cleanliness protocols are clearly noticed by the passengers (proven by the highest cleanliness rating possible) and deserve the five-star score awarded by Skytrax.

Chapter 5 – Conclusion and recommendations

5.1. Main conclusions

This research analyzed online reviews written by airline passengers using sentiment analysis, a well-established text mining technique capable of extracting information hidden in unstructured text (Sezgen et al., 2019). We successfully found what factors affect passengers' satisfaction, i.e., satisfaction dimensions, in the periods before and after the COVID-19 pandemic, but also the slight differences in passengers flying with LCC, FSC and different travel classes. Results also show that even before the pandemic, passengers were unhappy with the airline industry as a whole and their expectations were not being met. This general feeling aggravated even more during the pandemic.

Satisfaction dimensions were extracted and it was determined that the most mentioned dimension, before and after the pandemic, was concerning staff attitude. It is possible to conclude that staff behavior is the satisfaction dimension that has more impact on all passenger groups, regardless of the airline's business model.

We found out that FSC passengers, before the pandemic, gave importance to the airline's cabin crew, while LCC passengers gave more importance to the airline's customer service. However, both FSC and LCC passengers were displeased with topics linked to bookings and baggage. Regarding the type of cabin in which the passenger travels, we found out that Economy Class passengers' value and are pleased with the attitude and helpfulness of staff and cabin crew, but also show signs of being cost-conscious. Passengers flying in premium cabins also praise the attitude and helpfulness of cabin crew and staff, but also show sign of valuing the quality of the seating, food offerings and flight experience.

We also concluded that the COVID-19 pandemic did not bring many changes to the way passengers are satisfied. Comparing with the pre-COVID-19 period, the overall sentiment became more negative during the pandemic. We also verified some subtle differences in the satisfaction dimensions. Staff remained the principal dimension, but it was noted an increase of mentions regarding bookings and customer service within the FSC passengers. However, the main takeaway is that there was a surge of comments regarding refunds and aircraft cabin cleanliness, across all traveling classes. This is expected since the pandemic raised awareness about hygiene and caused the canceling of many flights.

5.2. Implications

5.2.1. Theoretical implications

For academia, this research contributes to the literature by revealing the factors that influence satisfaction of airlines' passengers. Moreover, this study was able to shed some light on how the pandemic affected airline passengers, revealing that passenger value cleanliness more nowadays than they used to, and that the class and business model influence the satisfaction factors.

5.2.2. Practical implications

From a managerial standpoint, airline companies can benefit from the created knowledge to adjust their strategies according to the created knowledge and meet their customers' expectations. Air companies are obligated to deeply understand the customer, not only to assure business growth, but also to develop service innovation and customer experience improvements (Siering et al., 2018), this study proves that sentiment analysis is a fast and cheap but effective way of gathering customer feedback. With this method, airlines can constantly monitor passenger reviews and improve their level of service according to the results, guaranteeing future customers and, in the end, revenue (Sezgen et al., 2019). There is also the advantage that airlines can use this method better understand the competition and use that knowledge to their advantage. Marketing strategies also benefit from this technology.

5.3. Limitations

Although this study encourages the use of user-generated content, it is vital to highlight some of its limitations.

The collection of reviews was carried out from only website (airlinequality.com), which leads to limited results. Additionally, all the reviews of the sample were written in English, meaning that the opinion of passengers speaking other languages is not being considered, skewing the sample even more. That might explain why most of the reviews are originated from English-speaking countries. Also, this study focused only on European airlines and other airlines might pose a different reality.

As mentioned throughout the study, sentiment analysis relies on identifying words. The algorithms are not prepared to deal with misspelled words, meaning that those words will not be recognized, and the final sentiment score might not be accurate. Also, the metadata used to complement the research data was also introduced by the passengers and it is not guaranteed that the information is correct as they are not subsequently validated (for example, wrong travel date).

5.4. Future work

For future work, it is recommended that a similar study be carried out in another part of the world. In addition, other attributes should be considered besides the class of travel and airlines' business model, such as short vs. long-haul passengers or type of travel (leisure/business).

To broaden and enrich the collected data, besides the website airlinequality.com, other review websites should be considered, such as tripadvisor.com, to examine if data varies significantly from website to website.

Finally, other industries should also be considered. It would be interesting to understand how COVID-19 affected, for example, the cruise industry. There is little to no data regarding passenger satisfaction in the cruise industry, let alone the influence of COVID-19 in said industry.

5.5. Communication

This dissertation has been adapted into a journal article and submitted to the prestigious **Journal of Air Transport Management.** It is currently pending approval.

The **Journal of Air Transport Management** covers, among others, the field of **Transportation (Q1)**. According to the SCImago Journal Rank (SJR), this journal has a ranking of 1.22 and an h-index of 75.

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Appendixes

Appendix A - Economy class mentions by sub-category and average sentiment polarity, during the pre-COVID period.

Economy Class	Number of mentions	Average sentiment polarity
Attitude	**3703**	**0,107854614**
Attitude	3703	0,107854614
Baggage	**4620**	**-0,188161144**
Baggage	2265	-0,188856155
Baggage-Attendant	27	-0,005925923
Baggage-Carry_On	152	-0,099867107
Baggage-Check_In	751	-0,09545757
Baggage-Cost	631	-0,100459084
Baggage-Management	641	-0,453278436
Baggage-Overhead_Cargo	118	0,00221479
Baggage-Under-seat_Storage	35	-0,0239156
Boarding	**2998**	**-0,009134054**
Boarding	2230	-0,017889561
Boarding-Assisted_Accessibility	71	-0,006798292
Boarding-Boarding_area_cleanliness	5	-0,400000054
Boarding-Process	692	0,021665472
Booking	**6326**	**-0,312306076**
Booking	1492	-0,116978745
Booking-Airline_Website	70	-0,064041957
Booking-Competitors	101	0,194074739
Booking-Fees	190	-0,297446916
Booking-Flight_Connections	233	-0,647370359
Booking-Layovers	99	-0,034363638
Booking-Scheduling	3297	-0,513364451
Booking-Ticket_Cost	492	-0,030763772
Booking-Ticket_Value	352	0,290392105
Cost	**3313**	**-0,007452668**
Cost-General	3313	-0,007452668
Customer_Service	**2519**	**-0,209492369**
Customer_Service	857	-0,362823964
Customer_service-Child_related_Needs	2	0
Customer_service-Children	338	-0,134884836
Customer_service-Compensation	320	-0,19782864
Customer_service-Frequent_Flyer_Rewards	53	0,054109023
Customer_service-Legal/Discrimination	7	-0,192857144
Customer_service-Lost_items	181	-0,572296658
Customer_service-Pets	9	-0,011111111

Customer_service-Pets-Pet_care	9	0,005555557
Customer_service-Premium_Options	226	0,021448468
Customer_service-Refunds	411	-0,142606087
Customer_service-Upgrades	106	0,452894001
Food_and_Drink	**5783**	**0,173519871**
Food_and_Drink	2815	0,102347113
Food_and_Drink-Alcohol-Cost	42	0,451300534
Food_and_Drink-Alcohol-Quality	56	0,609838099
Food_and_Drink-Alcohol-Variety	40	0,265330001
Food_and_Drink-Cost	702	0,0700433
Food_and_Drink-Options	136	0,024868162
Food_and_Drink-Quality	1106	0,434943865
Food_and_Drink-Quantity	307	0,077403148
Food_and_Drink-Variety	579	0,162826224
In_flight	**3115**	**0,077672826**
In_flight-Amenities-Price	7	0,028571427
In_flight-Bathroom-Cleanliness	95	-0,105415442
In_flight-Bathroom-Size	14	-0,389285728
In_flight-Cabin-Cleanliness	426	0,360718995
In_flight-Comfort	428	0,675691093
In_flight-Comfort-Noise	209	-0,304387877
In_flight-Comfort-Temperature	201	-0,449685497
In_flight-Comfort-Turbulence	66	-0,420223243
In_flight-Entertainment-Cost	106	-0,054886118
In_flight-Entertainment-Quality	505	0,283339793
In_flight-Entertainment-Variety	293	0,155735303
In_flight-Entertainment-Volume	17	-0,08333727
In_flight-Internet-Price	146	-0,143504198
In_flight-Internet-Quality	25	-0,604200015
In_flight-Internet-Speed	26	0,410276946
In_flight-Overhead_light	4	0,100000001
In_flight-Passengers-Attitude	33	-0,319808489
In_flight-Personal_devices	161	-0,136751288
In_flight-Power_ports	23	-0,117391306
In_flight-Runway_time	221	-0,290889524
In_flight-Weather_conditions	109	-0,55820108
Seating	**5292**	**0,055275869**
Seating	2463	0,01016605
Seating-Arrangements	170	-0,104732354
Seating-Business_Class	116	0,085244831
Seating-Economy_Class	580	0,085949716
Seating-Exit_row_seating	104	-0,139801539
Seating-First_Class	29	0,003083241
Seating-Leg_Room/Seat_Pitch	779	0,15391084
Seating-Premium_Economy	46	-0,007486958
Seating-Quality	1005	0,119844763

Staff	**14561**	**0,209126156**
Staff-Baggage_Attendant-Attitude	9	-0,163333322
Staff-Baggage_Attendant-Communication	3	0,100000001
Staff-Baggage_Attendant-Helpfulness	7	0,280000005
Staff-Baggage_Attendant-Knowledge	1	-0,480000019
Staff-Cabin_Crew-Attitude	1447	0,524966221
Staff-Cabin_Crew-Communication	250	0,061766293
Staff-Cabin_Crew-Helpfulness	911	0,631764123
Staff-Cabin_Crew-Knowledge	109	0,428637164
Staff-Cabin_Crew-Training	18	0,391111126
Staff-Customer_Service-Attitude	231	-0,325094253
Staff-Customer_Service-Communication	113	-0,166909739
Staff-Customer_Service-Helpfulness	394	-0,378165965
Staff-Customer_Service-Knowledge	82	-0,320618292
Staff-Customer_Service-Training	7	-0,408571436
Staff-Gate_Agent-Attitude	129	-0,204076644
Staff-Gate_Agent-Communication	39	-0,141646163
Staff-Gate_Agent-Helpfulness	64	-0,080258405
Staff-Gate_Agent-Knowledge	21	-0,15065714
Staff-Gate_Agent-Training	2	-0,600000024
Staff-General	4483	0,110182965
Staff-General-Attitude	2624	0,285825425
Staff-General-Communication	606	-0,049198737
Staff-General-Helpfulness	2291	0,31318873
Staff-General-Knowledge	318	-0,062838384
Staff-General-Training	66	0,044639403
Staff-Ground_Crew-Attitude	12	-0,053000006
Staff-Ground_Crew-Communication	5	-0,258000004
Staff-Ground_Crew-Helpfulness	18	-0,134500013
Staff-Ground_Crew-Knowledge	2	-0,355000019
Staff-Lounge_Staff	26	0,136576931
Staff-Lounge_Staff-Attitude	7	0,358214314
Staff-Lounge_Staff-Communication	3	0,413333337
Staff-Lounge_Staff-Helpfulness	5	0,034199995
Staff-Lounge_Staff-Knowledge	3	0,410000006
Staff-Pilot-Communication	133	0,106829354
Staff-Pilot-Knowledge	70	0,327361314
Staff-Pilot-Training	2	0,659999967
Staff-Sales_Agent-Attitude	1	-1,35800004
Staff-Sales_Agent-Communication	1	-0,960000038
Staff-Sales_Agent-Knowledge	1	-0,864000082
Staff-Ticket_Agent-Attitude	19	0,018052634
Staff-Ticket_Agent-Communication	15	-0,081333334
Staff-Ticket_Agent-Helpfulness	10	0,161800009
Staff-Ticket_Agent-Knowledge	3	-0,133333335

Total	52230	0,029823266

Appendix B – Premium Economy mentions by sub-category and average sentiment polarity, during the pre-COVID period.

Premium Economy	Number of mentions	Average sentiment polarity
Attitude	**225**	**0,353147649**
Attitude	225	0,353147649
Baggage	**152**	**-0,076549221**
Baggage	81	-0,093700211
Baggage-Attendant	3	-0,192000012
Baggage-Carry_On	3	0
Baggage-Check_In	28	0,004504161
Baggage-Cost	13	0,111153848
Baggage-Management	24	-0,210036711
Booking	**288**	**-0,239711038**
Booking	81	-0,070518519
Booking-Airline_Website	3	-0,266666671
Booking-Competitors	7	0,076000001
Booking-Fees	7	0,016594576
Booking-Flight_Connections	10	-0,572500005
Booking-Layovers	4	-0,229999997
Booking-Scheduling	128	-0,429722195
Booking-Ticket_Cost	14	-0,189250005
Booking-Ticket_Value	34	0,033117647
Cabin_Crew	**176**	**0,299188724**
Cabin_Crew	176	0,299188724
Cost	**161**	**-0,017755689**
Cost-General	161	-0,017755689
Customer_Service	**220**	**0,077993033**
Customer_Service	37	-0,390864867
Customer_service-Children	15	-0,173333334
Customer_service-Compensation	13	-0,05076923
Customer_service-Frequent_Flyer_Rewards	6	0,090000011
Customer_service-Lost_items	2	-0,540000021
Customer_service-Pets	3	0
Customer_service-Pets-Pet_care	1	0
Customer_service-Premium_Options	76	0,205782503
Customer_service-Refunds	20	-0,238000002
Customer_service-Upgrades	47	0,522148877
Food_and_Drink	**559**	**0,205115585**
Food_and_Drink	232	0,113504093
Food_and_Drink-Alcohol-Cost	2	-0,200000003

Food_and_Drink-Alcohol-Quality	10	0,643900004
Food_and_Drink-Alcohol-Variety	7	-0,057142858
Food_and_Drink-Cost	36	0,092934728
Food_and_Drink-Options	49	0,30179522
Food_and_Drink-Quality	130	0,44203334
Food_and_Drink-Quantity	46	-0,033136693
Food_and_Drink-Variety	47	0,183276602
In_flight	**267**	**0,260875253**
In_flight-Bathroom-Cleanliness	7	0,282857154
In_flight-Bathroom-Size	3	-0,877333323
In_flight-Cabin-Cleanliness	29	0,335445664
In_flight-Comfort	37	1,136338524
In_flight-Comfort-Noise	28	0,345614293
In_flight-Comfort-Temperature	8	-0,44250001
In_flight-Comfort-Turbulence	1	-0,300000012
In_flight-Entertainment-Cost	6	-0,425000007
In_flight-Entertainment-Quality	77	0,256926407
In_flight-Entertainment-Variety	39	0,067394267
In_flight-Entertainment-Volume	8	-0,039583348
In_flight-Internet-Price	2	-0,025
In_flight-Internet-Quality	2	-0,640000015
In_flight-Internet-Speed	1	-0,480000019
In_flight-Passengers-Attitude	5	-0,609000015
In_flight-Personal_devices	6	0,142666673
In_flight-Runway_time	4	-0,250000007
In_flight-Weather_conditions	4	-0,462499999
Seating	**873**	**0,198365575**
Seating	225	0,206638822
Seating-Arrangements	11	-0,018181818
Seating-Business_Class	38	0,027368422
Seating-Economy_Class	212	0,189655371
Seating-Exit_row_seating	3	-0,166666667
Seating-First_Class	6	-0,033333331
Seating-Leg_Room/Seat_Pitch	65	0,438062273
Seating-Premium_Economy	188	0,135042699
Seating-Quality	125	0,259763186
Staff	**852**	**0,328658931**
Staff-Baggage_Attendant-Attitude	1	-0,576000035
Staff-Baggage_Attendant-Communication	1	0
Staff-Baggage_Attendant-Knowledge	1	0
Staff-Cabin_Crew-Attitude	105	0,456265904
Staff-Cabin_Crew-Communication	12	-0,079166667
Staff-Cabin_Crew-Helpfulness	76	0,57820388
Staff-Cabin_Crew-Knowledge	5	-0,055502105
Staff-Customer_Service-Attitude	13	-0,364692321

Staff-Customer_Service-Communication	3	-0,783333311
Staff-Customer_Service-Helpfulness	17	-0,618647055
Staff-Customer_Service-Knowledge	8	-0,106249996
Staff-Customer_Service-Training	1	0,5
Staff-Gate_Agent-Attitude	2	-0,925999984
Staff-Gate_Agent-Communication	1	-2,088000059
Staff-Gate_Agent-Helpfulness	1	0,300000012
Staff-Gate_Agent-Knowledge	1	0,800000012
Staff-General	248	0,229985134
Staff-General-Attitude	160	0,448285043
Staff-General-Communication	22	-0,074027263
Staff-General-Helpfulness	149	0,531219431
Staff-General-Knowledge	13	-0,091962344
Staff-General-Training	1	0,5
Staff-Lounge_Staff	4	0,545000046
Staff-Lounge_Staff-Helpfulness	1	1,548000097
Staff-Pilot-Communication	4	0,062499985
Staff-Pilot-Knowledge	2	0,600000009
Total	**3773**	**0,186389303**

Appendix C - Business Class mentions by sub-category and average sentiment polarity, during the pre-COVID period.

Business Class	Number of mentions	Average sentiment polarity
Attitude	**886**	**0,636487384**
Attitude	886	0,636487384
Baggage	**488**	**-0,155488448**
Baggage	269	-0,158809225
Baggage-Attendant	3	-0,183333337
Baggage-Carry_On	6	0,066666668
Baggage-Check_In	56	-0,014214285
Baggage-Cost	35	-0,104933744
Baggage-Management	107	-0,260280375
Baggage-Overhead_Cargo	12	-0,057500002
Boarding	**622**	**0,146315471**
Boarding	447	0,145875407
Boarding-Assisted_Accessibility	12	0,110166666
Boarding-Boarding_area_cleanliness	2	0,600000024
Boarding-Process	161	0,144595753
Booking	**935**	**-0,183768326**
Booking	197	-0,047820599
Booking-Airline_Website	5	-0,019999999
Booking-Competitors	54	0,082506385
Booking-Fees	7	-0,117218803

Booking-Flight_Connections	30	-0,575000007
Booking-Layovers	34	-0,067876473
Booking-Scheduling	480	-0,340415794
Booking-Ticket_Cost	55	0,042138001
Booking-Ticket_Value	73	0,201400704
Cabin_Crew	**715**	**0,460074971**
Cabin_Crew	715	0,460074971
Food_and_Drink	**2308**	**0,354568472**
Food_and_Drink	987	0,278291766
Food_and_Drink-Alcohol-Cost	13	0,151538461
Food_and_Drink-Alcohol-Quality	75	0,545396785
Food_and_Drink-Alcohol-Variety	72	0,357923626
Food_and_Drink-Cost	90	0,112672225
Food_and_Drink-Options	43	0,20273582
Food_and_Drink-Quality	601	0,599771484
Food_and_Drink-Quantity	114	0,095472312
Food_and_Drink-Variety	313	0,270990911
In_flight	**945**	**0,094694899**
In_flight-Amenities-Price	5	-0,054659992
In_flight-Bathroom-Cleanliness	41	-0,122197566
In_flight-Bathroom-Size	12	-0,281666676
In_flight-Cabin-Cleanliness	87	-0,023673564
In_flight-Comfort	103	0,722254742
In_flight-Comfort-Noise	79	-0,014052545
In_flight-Comfort-Temperature	62	-0,442924205
In_flight-Comfort-Turbulence	10	-0,326200007
In_flight-Entertainment-Cost	21	0,15019048
In_flight-Entertainment-Quality	208	0,247556413
In_flight-Entertainment-Variety	157	0,135072805
In_flight-Entertainment-Volume	14	-0,288814295
In_flight-Internet-Price	42	0,077064089
In_flight-Internet-Quality	9	-0,420177788
In_flight-Internet-Speed	10	0,024920005
In_flight-Overhead_light	1	0,400000006
In_flight-Passengers-Attitude	8	-0,090500008
In_flight-Personal_devices	22	-0,197136369
In_flight-Power_ports	9	0,198666672
In_flight-Runway_time	31	-0,122258068
In_flight-Weather_conditions	14	-0,514225868
Lounge	**587**	**0,087761647**
Lounge	441	0,104271096
Lounge-Amenities	90	0,201688072
Lounge-Children	6	-0,073333348
Lounge-Cleanliness	29	-0,437397998
Lounge-Noise	21	0,024054716
Seating	**2492**	**0,068055357**

Seating	841	0,086721664
Seating-Arrangements	51	-0,08163255
Seating-Business_Class	726	0,001616971
Seating-Economy_Class	291	-0,029820526
Seating-Exit_row_seating	3	-0,466666679
Seating-First_Class	34	0,076235296
Seating-Leg_Room/Seat_Pitch	104	0,078944875
Seating-Premium_Economy	42	0,211642226
Seating-Quality	400	0,225092252
Staff	**3396**	**0,600078146**
Staff-Baggage_Attendant-Helpfulness	1	0
Staff-Baggage_Attendant-Knowledge	1	-0,400000006
Staff-Cabin_Crew-Attitude	446	0,760077136
Staff-Cabin_Crew-Communication	50	0,175304005
Staff-Cabin_Crew-Helpfulness	352	0,831161399
Staff-Cabin_Crew-Knowledge	22	0,329821286
Staff-Cabin_Crew-Training	8	0,329375014
Staff-Customer_Service-Attitude	44	0,003173322
Staff-Customer_Service-Communication	9	-0,025040001
Staff-Customer_Service-Helpfulness	53	-0,234981138
Staff-Customer_Service-Knowledge	10	-0,212600002
Staff-Customer_Service-Training	3	-0,133333335
Staff-Gate_Agent-Attitude	17	-0,263530812
Staff-Gate_Agent-Communication	4	-1,013420023
Staff-Gate_Agent-Helpfulness	11	0,34096972
Staff-General	898	0,427803628
Staff-General-Attitude	588	0,753467049
Staff-General-Communication	79	0,047706836
Staff-General-Helpfulness	616	0,8276807
Staff-General-Knowledge	44	0,062709094
Staff-General-Training	17	0,271500002
Staff-Ground_Crew-Attitude	3	-0,65422223
Staff-Ground_Crew-Communication	2	0
Staff-Ground_Crew-Helpfulness	2	-0,265333295
Staff-Lounge_Staff	44	0,504250013
Staff-Lounge_Staff-Attitude	18	0,674888911
Staff-Lounge_Staff-Communication	3	0,057600001
Staff-Lounge_Staff-Helpfulness	21	1,015955593
Staff-Lounge_Staff-Knowledge	4	0,330000013
Staff-Pilot-Communication	13	-0,069230765
Staff-Pilot-Knowledge	10	0,43000001
Staff-Ticket_Agent-Attitude	1	0,699999988
Staff-Ticket_Agent-Helpfulness	2	0,461999997
Total	**13374**	**0,291834457**

Appendix D - First Class mentions by sub-category and average sentiment polarity, during the pre-COVID period.

First Class	Contagem de Document ID	Média de Query Category Sentiment
Attitude	**101**	**0,884972027**
Attitude	101	0,884972027
Baggage	**56**	**-0,193044539**
Baggage	33	-0,118694761
Baggage-Attendant	2	-0,200000003
Baggage-Check_In	6	-0,150000002
Baggage-Cost	3	-0,266666671
Baggage-Management	9	-0,399285224
Baggage-Overhead_Cargo	3	-0,400000006
Boarding	**79**	**0,097962023**
Boarding	56	0,079267855
Boarding-Assisted_Accessibility	1	0
Boarding-Boarding_area_cleanliness	1	-0,720000029
Boarding-Process	21	0,191428568
Booking	**89**	**-0,210835961**
Booking	15	-0,02776
Booking-Competitors	11	0,214872733
Booking-Fees	1	-0,100000001
Booking-Flight_Connections	1	-1,800000072
Booking-Scheduling	49	-0,298563271
Booking-Ticket_Cost	4	-0,461500049
Booking-Ticket_Value	8	-0,292000011
Cabin_Crew	**97**	**0,539929128**
Cabin_Crew	97	0,539929128
Food_and_Drink	**250**	**0,408960807**
Food_and_Drink	112	0,24269286
Food_and_Drink-Alcohol-Cost	2	0,24000001
Food_and_Drink-Alcohol-Quality	12	0,799500023
Food_and_Drink-Alcohol-Variety	8	0,646750011
Food_and_Drink-Cost	3	0,237333337
Food_and_Drink-Options	2	0,200000003
Food_and_Drink-Quality	74	0,634881094
Food_and_Drink-Quantity	11	0,12363637
Food_and_Drink-Variety	26	0,398361542
In_flight	**107**	**0,139730098**
In_flight-Bathroom-Cleanliness	4	-0,048210002
In_flight-Bathroom-Size	4	0,001789998
In_flight-Cabin-Cleanliness	12	-0,481266675
In_flight-Comfort	10	0,888700014
In_flight-Comfort-Noise	7	0,474285741

In_flight-Comfort-Temperature	10	-0,251000008
In_flight-Comfort-Turbulence	1	-0,400000006
In_flight-Entertainment-Quality	30	0,339033343
In_flight-Entertainment-Variety	12	0,220333339
In_flight-Entertainment-Volume	3	0,200000003
In_flight-Overhead_light	1	0
In_flight-Passengers-Attitude	2	-0,400000006
In_flight-Personal_devices	3	0,133333335
In_flight-Power_ports	1	-0,400000006
In_flight-Runway_time	7	-0,142857143
Lounge	**86**	**0,215038764**
Lounge	66	0,260439398
Lounge-Amenities	10	0,513100013
Lounge-Children	3	0,233333339
Lounge-Cleanliness	6	-0,821111118
Lounge-Noise	1	0,400000036
Seating	**238**	**0,220129886**
Seating	84	0,134408732
Seating-Arrangements	1	0
Seating-Business_Class	25	0,028928366
Seating-Economy_Class	10	0,027600002
Seating-Exit_row_seating	1	-0,600000024
Seating-First_Class	81	0,256578149
Seating-Leg_Room/Seat_Pitch	2	0,100000001
Seating-Premium_Economy	2	0
Seating-Quality	32	0,616204379
Staff	**427**	**0,855047456**
Staff-Baggage_Attendant-Attitude	1	0,700000048
Staff-Baggage_Attendant-Communication	1	-0,100000001
Staff-Baggage_Attendant-Helpfulness	1	0,700000048
Staff-Baggage_Attendant-Knowledge	1	0,200000018
Staff-Cabin_Crew-Attitude	61	0,821449187
Staff-Cabin_Crew-Communication	3	0,366666675
Staff-Cabin_Crew-Helpfulness	47	0,973829798
Staff-Cabin_Crew-Knowledge	8	0,572500002
Staff-Cabin_Crew-Training	3	0,366666675
Staff-Customer_Service-Attitude	2	-0,656000018
Staff-Customer_Service-Communication	1	0
Staff-Gate_Agent-Attitude	4	0,050000004
Staff-Gate_Agent-Helpfulness	1	0,480000019
Staff-General	104	0,676673645
Staff-General-Attitude	74	0,960086495
Staff-General-Communication	4	0,495500028

Staff-General-Helpfulness	75	1,204477359
Staff-General-Knowledge	7	0,551942872
Staff-General-Training	4	0,175000004
Staff-Lounge_Staff	12	0,549916682
Staff-Lounge_Staff-Attitude	3	1,272333403
Staff-Lounge_Staff-Helpfulness	3	2,627000133
Staff-Pilot-Communication	4	0,545000017
Staff-Pilot-Knowledge	1	1,399999976
Staff-Pilot-Quality	1	1,399999976
Staff-Sales_Agent-Communication	1	0
Total	**1530**	**0,439934796**

Appendix E - Economy Class mentions by sub-category and average sentiment polarity, during the COVID period.

Economy Class	Number of mentions	Average sentiment polarity
Attitude	**350**	**-0,165616038**
Attitude	350	-0,165616038
Baggage	**362**	**-0,171059104**
Baggage	181	-0,189100548
Baggage-Attendant	3	0,133333335
Baggage-Carry_On	10	0,010000002
Baggage-Check_In	53	-0,137870652
Baggage-Cost	74	-0,11660989
Baggage-Management	32	-0,364062499
Baggage-Overhead_Cargo	5	-0,344000012
Baggage-Under-seat_Storage	4	0,277520005
Boarding	**190**	**0,00034569**
Boarding	158	-0,015631766
Boarding-Assisted_Accessibility	3	-0,366666665
Boarding-Boarding_area_cleanliness	1	1,200000048
Boarding-Process	28	0,086982146
Booking	**750**	**-0,219146108**
Booking	248	-0,094631214
Booking-Airline_Website	12	-0,050000001
Booking-Competitors	6	-0,059466685
Booking-Fees	34	-0,264098598
Booking-Flight_Connections	12	-0,675000002
Booking-Layovers	12	-0,330966671
Booking-Scheduling	334	-0,360890082
Booking-Ticket_Cost	72	-0,032500001
Booking-Ticket_Value	20	0,199700005
Cost	**373**	**-0,132161871**

Cost-General	373	-0,132161871
Customer_Service	**452**	**-0,194990529**
Customer_Service	140	-0,279774287
Customer_service-Child_related_Needs	1	0
Customer_service-Children	30	-0,194599998
Customer_service-Compensation	27	-0,173888894
Customer_service-Frequent_Flyer_Rewards	2	0,29400003
Customer_service-Legal/Discrimination	3	-1,130000015
Customer_service-Lost_items	13	-0,578461551
Customer_service-Pets	6	0,205182001
Customer_service-Premium_Options	11	0,080000002
Customer_service-Refunds	208	-0,175965019
Customer_service-Upgrades	11	0,579755763
Food_and_Drink	**312**	**0,049883752**
Food_and_Drink	147	0,032706566
Food_and_Drink-Alcohol-Cost	3	0
Food_and_Drink-Alcohol-Quality	4	0,745000005
Food_and_Drink-Alcohol-Variety	2	0,75
Food_and_Drink-Cost	36	-0,029531528
Food_and_Drink-Options	5	0,160000008
Food_and_Drink-Quality	55	0,170072733
Food_and_Drink-Quantity	18	-0,072222228
Food_and_Drink-Variety	42	-0,036071423
In_flight	**211**	**-0,035864757**
In_flight-Amenities-Price	1	0,400000006
In_flight-Bathroom-Cleanliness	3	0,166666667
In_flight-Bathroom-Size	2	0,075000003
In_flight-Cabin-Cleanliness	33	0,218793942
In_flight-Comfort	21	0,71400953
In_flight-Comfort-Noise	22	-0,430254558
In_flight-Comfort-Temperature	14	-0,269142864
In_flight-Comfort-Turbulence	7	-0,391766213
In_flight-Entertainment-Cost	5	-0,240000004
In_flight-Entertainment-Quality	19	0,285578965
In_flight-Entertainment-Variety	12	-0,095833339
In_flight-Entertainment-Volume	1	-0,800000012
In_flight-Internet-Price	16	-0,206712514
In_flight-Internet-Quality	4	-0,440000013
In_flight-Internet-Speed	1	0,400000006
In_flight-Passengers-Attitude	2	-0,433249995
In_flight-Passengers-Cleanliness	1	-1,450000048
In_flight-Personal_devices	30	-0,234600001
In_flight-Power_ports	4	0,125
In_flight-Runway_time	10	-0,241000003
In_flight-Weather_conditions	3	-0,400000006

Seating	**266**	**-0,07250942**
Seating	144	-0,135613236
Seating-Arrangements	13	-0,110076917
Seating-Business_Class	3	0,160000006
Seating-Economy_Class	26	0,001769234
Seating-Exit_row_seating	5	-0,220000005
Seating-First_Class	1	-0,600000024
Seating-Leg_Room/Seat_Pitch	30	0,095766674
Seating-Premium_Economy	1	0,800000012
Seating-Quality	43	-0,01923721
Staff	**1192**	**0,035729671**
Staff-Baggage_Attendant-Helpfulness	1	-0,300000012
Staff-Baggage_Attendant-Knowledge	1	0
Staff-Cabin_Crew-Attitude	85	0,503190887
Staff-Cabin_Crew-Communication	9	-0,233333343
Staff-Cabin_Crew-Helpfulness	60	0,752016675
Staff-Cabin_Crew-Knowledge	8	-0,141500007
Staff-Customer_Service-Attitude	26	-0,559230782
Staff-Customer_Service-Communication	19	-0,11142316
Staff-Customer_Service-Helpfulness	56	-0,530914288
Staff-Customer_Service-Knowledge	17	-0,588625882
Staff-Customer_Service-Training	1	0
Staff-Gate_Agent-Attitude	5	-0,603599989
Staff-Gate_Agent-Communication	1	-0,800000012
Staff-Gate_Agent-Helpfulness	5	-0,11559999
Staff-General	408	-0,014223569
Staff-General-Attitude	196	0,109130576
Staff-General-Communication	37	-0,071649734
Staff-General-Helpfulness	201	0,13601154
Staff-General-Knowledge	37	-0,52387117
Staff-General-Training	6	-0,133333335
Staff-Ground_Crew-Attitude	1	-0,400000006
Staff-Ground_Crew-Helpfulness	1	0,699999988
Staff-Lounge_Staff	1	0
Staff-Lounge_Staff-Attitude	1	-0,960000038
Staff-Lounge_Staff-Helpfulness	1	-0,960000038
Staff-Pilot-Communication	2	0,699999988
Staff-Pilot-Knowledge	2	0,800000012
Staff-Sales_Agent-Knowledge	1	-0,649999976
Staff-Ticket_Agent-Attitude	2	-0,900000006
Staff-Ticket_Agent-Communication	1	0
Total Geral	**4458**	**-0,087554167**

Appendix F – Premium Economy mentions by sub-category and average sentiment polarity, during the COVID period.

Premium Economy	Number of mentions	Average sentiment polarity
Attitude	**10**	**1,062200063**
Attitude	10	1,062200063
Boarding	**8**	**0,208100013**
Boarding	7	0,115771438
Boarding-Process	1	0,854400039
Booking	**13**	**0,035292502**
Booking	4	0,024999999
Booking-Fees	2	0,522601262
Booking-Scheduling	7	-0,098057142
Cabin_Crew	**7**	**0,725714292**
Cabin_Crew	7	0,725714292
Cost	**11**	**-0,166327059**
Cost-General	11	-0,166327059
Customer_Service	**9**	**0,147777786**
Customer_Service	2	-0,349999994
Customer_service-Children	1	0,400000006
Customer_service-Premium_Options	2	-0,049999997
Customer_service-Refunds	2	0,275000006
Customer_service-Upgrades	2	0,590000018
Food_and_Drink	**15**	**0,212773347**
Food_and_Drink	7	0,151028591
Food_and_Drink-Alcohol-Variety	1	0,650000036
Food_and_Drink-Cost	1	-0,0528
Food_and_Drink-Options	1	0
Food_and_Drink-Quality	3	0,429066668
Food_and_Drink-Quantity	1	-0,400000006
Food_and_Drink-Variety	1	0,650000036
In_flight	**8**	**0,287693761**
In_flight-Amenities-Price	1	-0,181650013
In_flight-Cabin-Cleanliness	1	1,100000024
In_flight-Comfort	2	0,768000036
In_flight-Entertainment-Cost	1	-0,720000029
In_flight-Entertainment-Quality	2	0,48360002
In_flight-Internet-Quality	1	-0,400000006
Seating	**25**	**-0,036319991**
Seating	6	0,021800006
Seating-Business_Class	2	-0,200000003
Seating-Economy_Class	6	-0,023466652
Seating-Leg_Room/Seat_Pitch	3	0,370666673
Seating-Premium_Economy	5	-0,268159992

Seating-Quality	3	-0,089733322
Staff	**42**	**0,50620003**
Staff-Cabin_Crew-Attitude	5	1,308000028
Staff-Cabin_Crew-Communication	2	0
Staff-Cabin_Crew-Helpfulness	2	0,659999996
Staff-Cabin_Crew-Knowledge	1	0
Staff-Customer_Service-Attitude	1	-1,5
Staff-Customer_Service-Communication	1	-0,699999988
Staff-Customer_Service-Helpfulness	1	-0,699999988
Staff-Gate_Agent-Attitude	1	2,234400272
Staff-Gate_Agent-Helpfulness	1	2,384400129
Staff-General	11	0,437018202
Staff-General-Attitude	7	0,951028628
Staff-General-Communication	3	-0,233333329
Staff-General-Helpfulness	5	0,183440018
Staff-General-Knowledge	1	0
Total Geral	**148**	**0,291699713**

Appendix G - Business Class mentions by sub-category and average sentiment polarity, during the COVID period.

Business Class	Number of mentions	Average sentiment polarity
Attitude	**53**	**0,409833973**
Attitude	53	0,409833973
Boarding	**42**	**0,234061914**
Boarding	31	0,18038065
Boarding-Process	11	0,385345478
Booking	**67**	**-0,254201488**
Booking	17	-0,207382349
Booking-Airline_Website	3	0
Booking-Layovers	3	-0,133333335
Booking-Scheduling	36	-0,328277771
Booking-Ticket_Cost	3	-0,166666669
Booking-Ticket_Value	5	-0,157599992
Cabin_Crew	**44**	**0,441118183**
Cabin_Crew	44	0,441118183
Cost	**38**	**0,080171189**
Cost-General	38	0,080171189
Customer_Service	**36**	**-0,129735471**
Customer_Service	11	-0,302043373
Customer_service-Children	3	-0,300000002
Customer_service-Frequent_Flyer_Rewards	4	0,100000001

Customer_service-Lost_items	1	-0,95599997
Customer_service-Premium_Options	5	0,009600013
Customer_service-Refunds	9	-0,144444442
Customer_service-Upgrades	3	0,453333348
Food_and_Drink	**120**	**0,03084819**
Food_and_Drink	59	-0,039883198
Food_and_Drink-Cost	5	0
Food_and_Drink-Options	2	-0,174999997
Food_and_Drink-Quality	22	0,339000002
Food_and_Drink-Quantity	11	0,126262872
Food_and_Drink-Variety	21	-0,11628572
In_flight	**44**	**0,287704543**
In_flight-Bathroom-Cleanliness	2	0,440000013
In_flight-Cabin-Cleanliness	3	1,593333304
In_flight-Comfort	6	0,656666684
In_flight-Comfort-Noise	2	0,685000002
In_flight-Comfort-Temperature	4	-0,200000003
In_flight-Comfort-Turbulence	4	-0,24000001
In_flight-Entertainment-Cost	1	0
In_flight-Entertainment-Quality	7	0,34885713
In_flight-Entertainment-Variety	4	0,237499982
In_flight-Entertainment-Volume	1	0,480000019
In_flight-Internet-Price	2	-0,449999988
In_flight-Internet-Quality	2	-0,352500007
In_flight-Internet-Speed	3	0,027333339
In_flight-Overhead_light	1	0
In_flight-Power_ports	1	0,100000001
In_flight-Runway_time	1	1
Seating	**127**	**-0,017959056**
Seating	46	0,046908695
Seating-Arrangements	1	0
Seating-Business_Class	45	-0,160875557
Seating-Economy_Class	14	-0,006714283
Seating-First_Class	1	0
Seating-Leg_Room/Seat_Pitch	3	0,033333331
Seating-Quality	17	0,164399996
Staff	**218**	**0,452893898**
Staff-Cabin_Crew-Attitude	27	0,633066683
Staff-Cabin_Crew-Communication	3	-0,124266644
Staff-Cabin_Crew-Helpfulness	22	0,42022727
Staff-Cabin_Crew-Knowledge	1	0
Staff-Customer_Service-Attitude	3	-0,680000017
Staff-Customer_Service-Communication	2	0
Staff-Customer_Service-Helpfulness	3	-0,607492357
Staff-Gate_Agent-Attitude	2	0,080000013
Staff-Gate_Agent-Communication	2	0,480000019

Staff-Gate_Agent-Helpfulness	1	0,960000038
Staff-General	57	0,407570581
Staff-General-Attitude	37	0,583297307
Staff-General-Communication	5	-0,113040036
Staff-General-Helpfulness	34	0,508530084
Staff-General-Knowledge	4	0,410000011
Staff-General-Training	2	0,574999988
Staff-Lounge_Staff	5	0,656000012
Staff-Lounge_Staff-Attitude	3	1,120000025
Staff-Lounge_Staff-Communication	1	1,440000057
Staff-Lounge_Staff-Helpfulness	2	0,520000026
Staff-Pilot-Knowledge	2	0,550000012
Total Geral	**789**	**0,183924439**

Appendix H - First Class mentions by sub-category and average sentiment polarity, during the COVID period.

First Class	Number of mentions	Average sentiment polarity
Attitude	**5**	**0,904633415**
Attitude	5	0,904633415
Boarding	**2**	**-0,300000012**
Boarding	2	-0,300000012
Booking	**6**	**-0,183976498**
Booking	1	0
Booking-Fees	1	0,446141005
Booking-Scheduling	3	-0,249999993
Booking-Ticket_Cost	1	-0,800000012
Cabin_Crew	**3**	**0,233333329**
Cabin_Crew	3	0,233333329
Check_In	**2**	**0,25**
Check_In	1	0
Check_In-Airline_Website-Quality	1	0,5
Cost	**3**	**-0,103333334**
Cost-General	3	-0,103333334
Food_and_Drink	**9**	**0,032577773**
Food_and_Drink	4	-0,134600013
Food_and_Drink-Alcohol-Cost	1	0,49000001
Food_and_Drink-Cost	1	0,49000001
Food_and_Drink-Quality	2	-0,074200004
Food_and_Drink-Variety	1	0
Lounge	**2**	**0**
Lounge	2	0
Seating	**8**	**0,258375**
Seating	3	-0,133333335
Seating-Business_Class	2	0,120000005

Seating-First_Class	3	0,742333333
Staff	**16**	**0,806916693**
Staff-Cabin_Crew-Attitude	2	0,650000006
Staff-General	5	0,81760003
Staff-General-Attitude	4	1,172291733
Staff-General-Helpfulness	3	0,944499999
Staff-Lounge_Staff	1	0
Staff-Lounge_Staff-Helpfulness	1	0
Total Geral	**56**	**0,338931698**

Appendix I – Description of mentioned categories, in order of appearance.

Category name	Description
Staff	Airport/airline employees
Seating	Seating in the aircraft
Food_and_Drink	Food and beverages available at the airport or on the aircraft
Baggage	Passenger's checked baggage
Booking	Procedures related to booking an airline ticket
Customer_Service	Activities related to the airline's customer service
Check_In	Procedures related to checking-in for a flight
Cabin_Crew	Airline personnel onboard the flight
In_Flight	Activities that occurred in-flight
Cabin_Crew-attitude	Attitude of the airline personnel onboard the flight
Staff-Helpfulness	Helpfulness of airport/airline employees
Cost	Cost of the fare
Baggage-Cost	Cost of checked baggage
Seating-quality	Quality regarding the airplane seat
In_flight-quality	Quality of the flight
Lounge	Airport lounge for passengers traveling in Business or First Class
Attitude	Attitude of airport/airline employees
Customer_Service-refunds	Regarding refund requests through an airline's customer service
In_Flight_Cabin-cleanliness	Cleanliness of the aircraft cabin