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A Methodology for Machine-Learning Content Analysis to Define the Key Labels in the Titles of Online Customer Reviews with the Rating Evaluation

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Abstract: Online reputation is of great strategic importance to companies today. Customers share their emotions and experiences about the service received or the product acquired through online opinions in the form of quantitative variables or text comments. Although quantitative variables can be analyzed using different statistical methods, the main limitation of comment content analysis lies in the statistical analysis because the texts are qualitative. This study proposes and applies a methodology to develop a machine learning designed to identify the key labels related to the quantitative variables in the general rating of the service received from an airline. To this end, we create a quantitative dichotomous variable from zero to one from a database of comment title labels, thus facilitating the conversion of titles into quantitative variables. On this basis, we carry out a multiple regression analysis where the dependent variable is the overall rating and the independent variables are the labels. The results obtained are satisfactory, and the significant labels are determined, as well as their signs and coefficients with the general ratings. Findings show that the significant labels detected in titles positively influence the prediction of the overall rating of airline. This paper is a new approach to applying cluster analysis to the text content of customers' online reviews in an airline. Thus, the proposed methodology results in a quantitative value for the labels that determines the direction and intensity of customers' opinions. Moreover, it has important practical implications for managers to identify the weakness and the strengths of their services in order to increase their positioning in the market by developing meaningful strategies.

Keywords: machine learning; content analysis; online customer review; airline; sentiment analysis; key label; artificial intelligence; social media

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1. Introduction

The online reputation of a company, brand, product, or service is composed of a set of opinions, experiences, and evaluations that customers share through different social media [1]. Online reputation is extremely important in a company's strategy because customers increasingly use information obtained on the Internet to make decisions about buying services such as those provided by hotels or airlines [2–9]. Moreover, the information available on the Internet about the quality of services and the value perceived by customers, both of a given company and its competitors, is quite relevant for measuring the degree of compliance with the objectives established [10–14]. Specific authors, such as Chun [15] and Hernández Estárico et al. [16], recognize that the online reputation is an effective means of measuring the level of service quality perceived by customers and their degree of satisfaction, and it also has a direct influence on the level of companies' income and profits [17].

The online reputation on specialized websites such as TripAdvisor is determined through two means. On the one hand, websites obtain information from customers using a scale of quantitative variables that measure the perceived quality of the service and customers' perceived value [1,18,19]. According to Torres [20], service quality is a process oriented towards an evaluable result, and so service quality is assessed through items that measure its main attributes. In contrast, this author also points out that customer satisfaction is an overall evaluation of a user's experience or emotions with the service received. From this perspective, customer comments are qualitative variables used to evaluate customer satisfaction [21]. Hence, companies give great importance to classifying the content of online reviews in order to take measures to strengthen the relationship with their customers [22].

The airline industry needs to continuously analyze the online customer reviews on its service. previous studies demonstrate that online reviews shared by consumers are more persuasive than information shared by marketers, as customers have no interest and are therefore more credible and independent [23–26].

According to Araque et al. [27], the increase in user-generated content (UGC) on websites and social media such as TripAdvisor, Facebook, or Twitter has enhanced social media's influence on decisions to purchase services, products, or brands. The analysis of content has become an essential tool for companies to use to find out their customers' assessments, developing different techniques such as Sentiment Analysis [22,28,29], whose purpose is to classify the opinions and feelings expressed by users in text comments. Sentiment analysis involves determining the meaning and intensity of what is expressed in a text, which may be a positive, negative, or neutral feeling (or polarity) about a particular product or service [30]. Some authors have based their sentiment analyses on machine learning approaches, where an assessment is made of the words that influence the polarity and intensity of users' comments [31–33]. In the airline industry, online feedback from customers is also becoming crucial because it determines their satisfaction with the basic dimensions of the service offered [34].

The majority of studies have focused on the influence of online customer reviews on customer's decisions. A few investigators have attempted to examine some different methods to use intelligence extracted from UGC to gather information for an organization [35,36]. This study fills this gap and aims to propose a methodology for performing machine learning, based on determining the key labels that drive customers' online ratings in an airline. The process consists of different stages that start with the creation of a database of labels, in order to later quantitatively evaluate their relationship with the general rating variable on TripAdvisor. Through descriptive and multiple regression analyses, key labels related to the overall rating, sign, and intensity are established. Cluster analysis is also carried out to test whether groups of clients can be identified based on the vocabulary they use in their comments. A review of the specialized literature is first carried out to achieve this objective, and then the proposed methodology is described. The following section shows the results obtained, ending with a description of the main conclusions reached.

2. Literature Review

Airlines use content analysis of online (positive or negative) reviews to evaluate customers' satisfaction. Travelers can write their comments and post online ratings to describe, narrate, recommend, or criticize their travel experiences [37–39]. Reviewers use and evaluate products or services and disseminate their evaluations, making them an early link in an innovative diffusion process [40]. Reviews are especially important when a product or service has substantial experience attributes, making it difficult to carry out pre-consumption quality assessment. Clients seek purchase recommendations from external sources [40,41]. Marketers also want to understand the significant and predictive powers of reviews. Knowing whether reviews are positive or negative allows marketers to forecast their products' sales. The airline industry is one of the essential factors in Tourism competitiveness because companies have to deal with various challenges, such as fuel prices, increasing security precautions, low-cost carriers, economic crisis, and restrictive government regulations [42,43]. It is crucial for managers of airlines to not only correctly perceive what their customers want and expect, but also to appropriately manage their resources in meeting their customers' expectations [44–49]. If reviews are aggressive, corrective measures, such as revising promotional strategies or redesigning the brand, may be instituted [50].

In the airline industry, various studies have been dedicated to investigating the relationship between service quality and related issues such as customer satisfaction and brand [34,51–56]. Farooq et al. [55] had studied the quality of service in Malaysia airlines using second generation PLS-SEM tools to get robust results, their findings showed that airlines should focus on all aspects of service quality, with particular focus on image and personnel service in order to enhance their customer satisfaction. Research from Noviantoro and Huang [57] using data mining method to examine U.S airline passenger satisfaction mention that (1) online boarding, (2) inflight Wi-Fi service, (3) baggage handling, and (4) inflight entertainment are the principal four services to be improved by the airline to gain passenger satisfaction. For any airline, these are the main factors in overcoming the economic crisis by understanding and facilitating flexible new ways of dealing with their customers, such as rapid response on social media, airline refunds, and flight change and overbooking policies [58–61]. From this perspective, many researchers have proposed various scales to examine the service quality in the aviation industry with different aspects such as courtesy of staff, seat comfort, empathy and reliability, ground staff, flight experience, flight schedule, inflight comfort, flight timeliness and airline image [62–68].

Online reviews and overall ratings form part of the most common UGC models [11]. A review is a sample of textual opinion that describes the traveler's experience with the airline in a qualitative manner [69]. Unlike a review, the rating is based on a five-point scale, measured in a quantitative way that describes whether and to what extent a customer is satisfied with the airline [70]. Investigated together, review and rating can design a complete traveler response image and synergistically maximize analysis validity [71,72]. However, showing the relationship between online reviews and general ratings is a complicated task because the two sources of data are typologically different. Whereas rating data can be measured using the simple model consisting of structured and quantitative numbers that can efficiently be measured using statistical tools [73], reviews consist of natural language and sentiment summarization. This means that reviews are disorganized and qualitative, which makes it difficult to understand and analyze them using traditional tools [74–77].

The relationship between customer ratings and reviews, facilitated by the quantification of textual review, has also been analyzed in customer satisfaction studies (Table 1). For instance, Büscken and Allenby [72] correlated the frequency of customer review topics with ratings using multiple linear regressions. In line with this study, if the coefficient of the frequency of a topic is positive, the customers are relatively satisfied with it, and so more frequently mentioning this topic will lead to a positive increase in the rating. Hao et al. [78] successfully distinguished satisfactory titles (topics) from unsatisfactory ones by comparing the appearance of topics associated with positive and negative ratings. In sum, managers can discover not only whether consumers are happy or unhappy, but also why, which has provided an essential methodological foundation for this investigation.

Class differentiation is the main problem of Sentiment Analysis that is being addressed by learning machine algorithms. At first, it is much easier to differentiate between a negative and positive opinion than between a negative and very negative one. Moreover, this latter difference may be more precise for one person than for another because these evaluations are subjective. The solution to this type of problem is to define the critical characteristics of the text that contribute to identifying the difference between them in each of the defined classes. To do this, Insúa Yáñez [79] used two main approaches. The first is the Bag of Words (BOW) model, which is the simplest and is based on the creation of a vector of characteristics where each variable corresponds to a word in the domain. Its value is a series of occurrences in the text or a statistical value that reflects the word's relationship with its context. Some of the machine learning methods applied are Naïve Bayes [80], K-nearest neighbor [81], Maximum Entropy [82], Adaboost [83], Decision Tree [84], Winnow [85], and Support Vector Machine [86].

In the absence of a label database, a sentiment classification model can be constructed based on a lexicon that defines the words' polarity [32]. Depending on the terms' frequency, a document will be classified as positive, negative, or even neutral. An additional method proposed by Liu et al. [87] is the lexicon-based sentimental classification model with unlabeled data that defines words' polarity in a semi-supervised learning model. Another alternative that has been developed is the ensemble technique, where the results of various classification models are combined to arrive at an integrated result [88]. The other approach is Word Embeddings (WE), where a composed vector is created through training in a neural network that receives a broad set of texts as input and tries to learn the similarity relations between the words they contain. Each word's result is a vector of real digits of a given length, which facilitates the search for similarity relations, or even addition and subtraction operations between the vectors that represent the words, yielding another word as a result [89,90].The methodology applied in this study does not start from any initial lexicon that indicates the meaning of the words. Moreover, a database is created from the words used by airlines users in the titles of online comments on TripAdvisor. Next, the database is debugged, and a vector-based numerical database is created with dichotomous variables (zero and one). This database is used to carry out a linear regression where the dependent variable is the overall rating and the independent variables are the labels. This provides a sense of each significant label, measured by a positive or negative sign, and the intensity evaluated by the coefficient is obtained.

Table 1. Recent research on overall ratings from online reviews in the aviation industry and tourism.

Study	Variables	Research Context	Key Findings
Chang et al. (2022) [91]	Online reviews & Overall ratings of airlines	TripAdvisor 191,123 reviews	- Analyze airline reviews and understand passenger satisfaction before and during COVID-19 - This study applies BERT to learn linguistic features and aspect level ratings. - Findings reveal that both review and ratings drop significantly during the pandemic.
Dhar & Bose (2022) [92]	Online reviews & Star rating	Mobile app 146,914	- Sentiment and emotion analysis of the review text and reaction analysis of the emojis. - The consolidated sentiment and happiness emotion in reviews strongly impact their star ratings. - The proposed perception score closely reflects the emotions, sentiments and reactions embedded in the reviews.
Stamolampros et al. (2020) [93]	Online reviews of Airlines& average airline ratings	TriAdvisor 380,000 reviews	- Passengers express higher overall rating for domestic carriers than international carriers. - Using Hofstede's framework shows that cultural dimensions affect the intensity of domestic bias.
Park et al. (2020) [56]	Online reviews of Airlines & overall satisfaction ratings	TripAdvisor 157,035 reviews 20 U.S airlines	- The quality of airline service, such as cleanliness, food and beverages, and inflight entertainment, affects the variation of positive ratings as a satisfier. - Other airline service attributes, such as customer service and check-in and boarding influence negative ratings as a dissatisfier.

Table 1. *Cont.*

Study	Variables	Research Context	Key Findings
Lucini et al. (2020) [34]	Online reviews of Airlines & overall satisfaction ratings	Air travel review ATR	- OCRs can be used to measure customer satisfaction - Airline recommendation by customers was predicted with an accuracy of 79.95%
Song et al. (2020) [94]	Online sentiment reviews & the ratings of airlines	SKYTRAX 24,165 online reviews	- User sentiment analysis show that there is a significant and negative correlation between the users' emotions and their flight delay experiences. - Sentiment analysis based on a sentiment dictionary is used to classify user reviews. - Co-occurrence analysis is used to identify passengers' concerns on different aspects of service in the aviation industry.
Sharma et al. (2020) [95]	User sentiment review &overall review of flight	TripAdvisor 157,036 reviews 20 US airlines	- It analyzes the relation between ratings and review sentiment by using prospect theory. - Variations in ratings closer to the reference point result in higher marginal impact on sentiment than equivalent variations.
Tsai et al. (2020) [96]	Online hotel review & The overall ratings	TripAdvisor 1009 US hotels 23,430 reviews	- Proposed a novel approach to generate high quality summaries of online hotel reviews. - Both review helpfulness and hotel features were considered before review summarization. - Online hotel reviews were collected in experimental evaluation.
Korfiatis et al. (2019) [97]	Online reviews of Airlines & overall satisfaction ratings	TripAdvisor 557,208 reviews	- Using (STM) structural topic model, the review text is coupled with numerical ratings. - Online reviews give a solution through quality features which better predict variation in passenger preferences and competition.
Sezgen et al. (2019) [53]	Online reviews of airlines	TripAdvisor 5120 reviews 50 airlines	- Using (LSA) Latent Semantic Analysis, findings show that passenger satisfaction and dissatisfaction dimensions differ depending on airline service class - Friendly and helpful staff, value and low fares are the main important factors for economy and Premium class passenger.
Punel et al. (2019) [98]	Online reviews Airlines ratings	Skytrax 40,510 reviews	- The geographical regions shaped by the country of residence of passengers impact travel experiences, perception, and evaluation of airline services. - North American passengers complain more about their national airline. - Americans care more about money and less about in-flight services.
Siering et al. (2018) [99]	Online reviews & Overall airline rating	Airlinequality.com 1000 airlines reviews 195 airlines	- Explanation of service recommendation based on core and augmented service aspects. - Prediction of the recommendation decision by means of machine learning techniques. - Analyze the role of airline service models (low cost vs. full service carriers.

3. Research Methodology

These three steps will be followed to obtain and process the necessary information to achieve the proposed research objectives: (1) Obtain the online customer reviews from the specialized website; (2) prepare the database from the information obtained; and (3) perform the statistical analysis of the database. Regarding the first step, the study was carried out based on the online opinions of 5278 customers about Iberia airline in the period of 2016–2018. All the comments were made in the Spanish language, but the methodology developed in this article is indifferent to the type of language used, as in the case of English. Customers are mainly from Spain and Latin American countries. The data were obtained from the TripAdvisor website, where information is provided on the general rating given by the customer, the title, and the comment. The general rating is a quantitative variable with five options ranging from poor to excellent (1—poor; 2—bad; 3—normal; 4—very good; 5—excellent). The title is made up of a limited number of words that describe the general meaning of the user's opinion, whereas the comment presents all the aspects the customer wants to highlight, whether positive or negative. Both the title and the comment are qualitative variables that must be treated in a content analysis. To this end, a methodology and software have been designed to treat the information and prepare it for statistical analysis in quantitative terms.

The second step in the methodology consists of elaborating the database in order to treat it statistically. This requires, first, creating the labels from the words used in the titles of the reviews. Second, all the labels that are not considered relevant to the general rating must be deactivated, as in the case of the articles the, a, or an, or verbs such as to be or to have, for example. Third, it is necessary to define whether the labels will be integrated depending on the words detected in the titles or the words' root. The latter makes it possible to reduce the number of tags because, for example, singular and plural words will be assigned to the same tag. Likewise, regular verbs or superlatives should also be assigned to the same common root. In this context, lemmatization is the way words are reduced to their elemental form, excluding final inflections [100]. Generally, because the software was developed in English, a specific program adapted to the Spanish language is used in this study. Finally, a database is created where each row is a review, and the columns represent the total number of labels, so that if a label is in the title of the comment, it will be assigned a one, and if not a 0. This is a method of converting a text into a vector of dichotomous variables, 0 or 1, that can be treated with quantitative statistical procedures. In this context, vector space models (VSMs) represent words as a vector in multidimensional space. An incredibly efficient model from a computational point of view is Word2vec, where the texts are transformed into vectors. Therefore, if a text includes a specific word, its variable is given a value of 1, and otherwise a value of 0 [101].

Finally, a database is created where each row is a comment and the columns show the total number of labels, so that if a label is in the title of the comment, it will be assigned a 1, and if not a 0. This is a method of converting a text into a vector of dichotomous variables that can be treated with quantitative statistical procedures. In this study, 2567 labels were detected once the irrelevant ones had been deactivated. To simplify them, we developed a program where the labels were assigned to the same root. To do so, first, the plurals or endings of regular verbs were eliminated. Second, a minimum number of characters was determined to form a common root because, if a minimum number is chosen, the program can detect many coincidences. For example, if we are not searching for similar words, the "bad" label can be detected in multiple words that start with bad, such as badminton. Therefore, the program was set to search for tags based on the root when it has six characters or more. If the tag has five or fewer characters, the text is searched for similar words. Using this method, we reduced the labels to 1523.

Once the databases have been created, three types of statistical analyses are carried out. The first analysis is to determine the number of times each label appears in the titles of the comments. Next, the average of the ratings obtained in the titles of reviews where each label appears is obtained, and so it is possible to evaluate to what extent it has a positive influence, that is, it obtains an average of more than 3, or a negative influence when it achieves an average of less than 3. The second statistical analysis is linear regression, where the dependent variable is the overall rating and the independent variables are the labels. This multiple regression analysis is carried out for the database of all the labels and the roots of the labels. The results allow us to determine if there is a significant relationship between each of the labels and the comment's overall rating. Finally, cluster analysis with the significant variables is carried out to test whether users can be classified according to the types of words in their online comments. Confirming clusters among significant users would be a first step in determining whether the type of vocabulary used by different users is similar.

Based on the above, the machine learning model proposed in this article to determine the key labels related to overall online customer ratings follows these steps (see Figure 1):

(1) Obtaining customers' online reviews containing their general rating, title, and comment shared on a social network.
(2) The tag database with the words contained in the titles of the comments could also be created with the comments themselves, but the number of tags would increase enormously, which would make the statistical study difficult. Furthermore, it can be assumed that the most relevant words to define the customer experience are found in the titles.
(3) Debugging the labels to deactivate those that do not directly impact the sense of the customers' online ratings. This task must be carried out by a specialized team or person who will transfer their knowledge to the machine learning system as the number of labels increases. From here, the final database of the labels to be used in the statistical analysis will be obtained.
(4) Create a numerical database where each row corresponds to an online comment from the customers and the columns correspond to the variables that, first, consist of the general rating given by the customers (variables between 1 and 5). In contrast, the rest of the variables are the active labels, which will be given a value of 1 if they are found in the title of the comment, and 0 otherwise.
(5) If necessary, create a new numerical database of labels based on the root of the words to reduce the number of variables without losing the meaning of the words.
(6) Conduct a linear or other type of regression if considered necessary, where the dependent variable is the general rating and the independent variables are the activated labels. A descriptive analysis is also carried out of the averages of the general rating obtained in titles with the same label, which helps to relate the meaning and intensity of the tags to the general rating.
(7) Check whether the regression model is consistent through the adjusted R square obtained. Likewise, the labels with a significant relationship, positive or negative, with the general rating will be determined. Furthermore, the minimum number of times a label appears can be established for use in subsequent analyses. By establishing the significant labels and the minimum number of times they have to appear in the titles or comments, a final database of significant labels can be created.
(8) Once the meaningful labels have been determined, cluster analysis can be conducted to check whether a classification is adequate. The variables would be the labels, initial, root, or significant, as decided in the research, resulting in a classification of customers according to the types of words they use in their titles or online comments.
(9) Continue to obtain information from new online customer reviews.
(10) Verify whether the words in the new titles are already in the original label database. If so, the next step is to be taken. If not, a new label will be created and evaluated to determine whether it should be deactivated, depending on its impact on the customers' general assessment. Once these decisions have been made, the next step is carried out.
(11) Assess whether the words in the title of the new review correspond to any significant label. If so, an overall rating can be predicted. In this case, the difference between the predicted rating and the actual rating is evaluated to establish how accurate the

prediction is. Another statistical analysis that can be performed in this step is to assign the new customer who makes the online comment to one of the predefined clusters to classify the user and start to define a profile based on the words s/he uses.

(12) When a relevant number of predictions have been made, a joint analysis is carried out to validate the regression model applied and the assignment of users to predefined clusters.

(13) When a significant number of new online reviews have been added, we move to Step 4 to perform a new regression analysis to confirm whether the labels are still significant, whether they maintain the coefficients, and whether there are new labels that are significant. A new cluster analysis can also be carried out to check whether the defined clusters are still maintained or, conversely, have to be reidentified because substantial changes have occurred. A comparative analysis is performed to determine whether there are changes in the vocabulary used by customers to assess the service received.

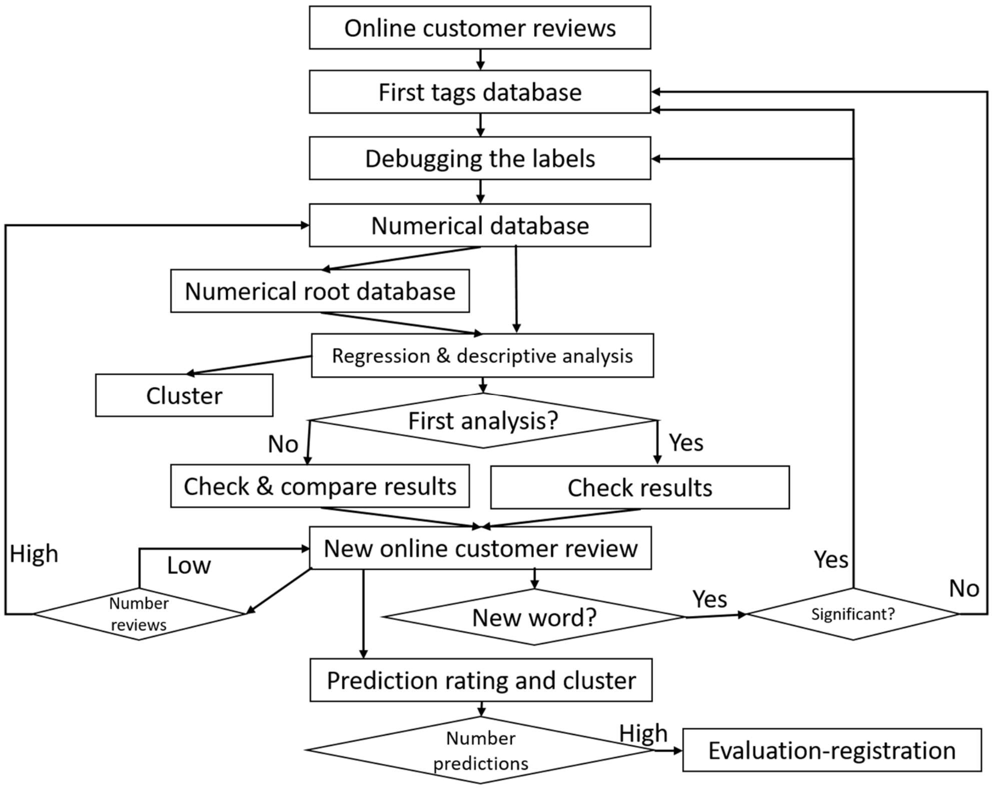

Figure 1. Machine learning model of significant labels in online customer reviews.

In this study, the proposed machine learning model's primary application is carried out to detect the key labels that significantly influence the overall rating of online customer reviews. This is the essential part of the model because introducing new comments would involve detecting whether they incorporate the significant labels and, therefore, whether the rating assessment can be predicted. All activities related to the feedback of new data are not covered in this article, although from a practical perspective, they are relatively simple to solve using software.

First, detecting whether a new word in a title or comment is listed in the first tag database only requires a search. If it is found, nothing else has to be done. However, if the word is not in the database, it has to be included, and a specialist will have to determine whether or not it is significant in predicting the overall rating. In this part of the process, currently available knowledge from a specialized person is transferred to machine learning. As the vocabulary increases, the system will automatically detect whether a word is to be activated or deactivated. Once the new word enters the first database as off, or in the debugger as an active label, the system prepares to perform a new statistical analysis when it reaches a certain number of new online reviews.

Another function to be performed in new research is predicting a new online review. Knowing the labels significantly related to the general rating and their coefficient could establish a prediction of the possible rating given by the user making the comment. The next step is to carry out a simple comparison with the user's real rating, data that will be integrated into the existing database as two new variables, that is, the predicted rating would be one variable and the difference from the real rating the other. When a certain number of new comments is reached, a joint analysis of the variable where the differences are collected will be conducted to determine whether an acceptable level of success has been achieved. Finally, once a certain number of new comments have increased the database, the statistical analysis will be performed again to assess whether the labels are still meaningful or any new ones should be added. The new coefficients will also be calculated and compared with the existing ones, which will determine whether there are changes in the intensity with which users use their words to rate the service. A new database must be created to perform this function, or variables must be added to the database of already existing labels, specifying the level of significance, the coefficient obtained, and the date on which the statistical analysis is conducted. With this information, it is relatively simple to elaborate on comparative reports.

4. Analysis of Results

The analysis to validate the proposed model has two parts. In the first part, a descriptive analysis of the labels is carried out to determine the number of times they appear and the average value of the rating obtained in these comments. Second, a multiple regression analysis is conducted with the labels created from a 6-character word root, i.e., a label is considered a root when it has six or more characters; in other cases, the label is treated as a word. Finally, a cluster analysis is performed to check whether user groups can be identified based on the type of vocabulary used to write their feedback online.

4.1. Descriptive Analysis of the Labels

The first analysis is descriptive, and the labels have been chosen that appear in at least three different comment titles. The purpose of this study is, first, to determine the number of times a tag appears in a title. This allows us to establish how often it is used and whether it is a word that is employed a lot or a little to describe customers' perceptions. Second, the average of the reviews' general ratings for each label detected in their titles is a fascinating index because it gives us a clue as to where user ratings are oriented. Considering that the mean value of the overall rating is 3, all averages that are significantly higher will indicate that the label is used in positive feedback titles. Conversely, if the average is below 3, the label is usually found in negative comments.

This analysis allows us to detect the key labels that direct a customer's assessment toward a positive, negative, or neutral pole. Hence, the next step is to determine whether the relationship between a label's appearance in a title and the general rating is significant. This will be done in the following section, where a multiple regression analysis will be performed. Regarding the results obtained in Appendix A, it can be seen that there are more significant labels above the average of 3 than below it. In order to simplify Annex A, we have chosen to represent only those labels that have been used in at least three different comments.

The descriptive analysis conducted is very enlightening because it obtains the average rating from user ratings where each label appears. As Appendix A shows, the pleasure, notable, and printing labels are found in comments where the average rating is 4.75, confirming their direct relationship with a high rating of the service received. It can be seen that the rest of the adjectives and words that are linked to a positive aspect of the brand or the service received obtain an average rating above 4. On the other hand, the labels linked to ratings below 1 are chaos, avoidance, unpresentable, motive, terror, and thrown away. Another aspect highlighted is that a significant number of labels are positioned in intermediate rating averages, which either means that they are not the key labels to define the rating's orientation and intensity or that they are linked to a neutral rating.

Another exciting fact shown in Appendix A is the number of times a label appears in the comments' titles. These data are complementary to the previous ones because if a label is used a lot and related to a specific rating, it would confirm the rating obtained. For example, the label excellent appears in 327 comments with an average rating of 4.64, and the word punctual is used in 468 comment titles with an average rating of 4.15, which denotes a relationship with positive aspects of the airline. In contrast, labels such as pessimistic appear 45 times, with an average rating of 1.47, and baggage appears 51 times, with an average rating of 2.24, which means that when a customer remembers baggage, it is because something has not gone as expected.

4.2. Regression Analysis

In this step, a multiple regression analysis is performed where the dependent variable is the rating, and the independent variables are the labels. The purpose is to establish the tags that are significantly related to the rating. The regression analysis has a double advantage over other types of prediction methods, such as neural networks. On the one hand, it determines which labels are significant and which are not, so that key labels can be identified. On the other hand, it gives a coefficient as a result, indicating the direction of the relationship, positive or negative, and the intensity of the relationship based on the size of the value.

Appendix B shows the significant labels at 5% and 10%, with a total of 369. Likewise, the adjusted R square was 0.546, which is a high value in the social sciences. Therefore, it can be stated that the relationships obtained between the labels and the ratings are consistent and demonstrate a logic between the words used to describe the service or image of the airline and the quantitative assessment reflected in the customer's rating. The adjusted R square of the original labels is 0.614. As can be seen, this is a higher result than for the root of the labels, but the latter is also satisfactory and allows for a simplification of the content analysis.

In Appendix B, the labels have been organized according to the coefficient achieved, from highest to lowest. Among the labels with positive coefficients, there are labels with the root of places, maintain, congratulations, relax, personalized. It should be emphasized that there are labels, such as wrong, whose meaning can change when there is a word of negation next to it; for example, you are not wrong. In addition, some labels have a positive sign, such as indecent, which appeared only once or twice, because it is not found in the descriptive analysis. In contrast, labels with a negative coefficient include disappointment, rudeness, or defect.

4.3. Cluster Analysis

The K-means cluster analysis was performed using the significant tags. This study can be considered exploratory because this type of study has not usually been carried out from this perspective. For this reason, we decided to define five clusters because the rating variable has five response alternatives. It is necessary to highlight that the formation of clusters from the type of words used by users to share their opinions may be a more complex analysis. However, it is a first step that offers us alternatives and suggestions for developing future, in-depth research on this exciting topic. Therefore, it should be considered a first approach to applying cluster analysis to the text content of customers' online opinions.

The number of cases assigned to these five clusters was as follows: Cluster 1, 598 cases; Cluster 2, 600 cases; Cluster 3, 129 cases; Cluster 4, 617 cases; and Cluster 5, 3334 cases. As can be seen, Cluster 5 has a very high number of cases, which means further research into the characteristics of this cluster is needed in order to identify possible new criteria for classifying clients. However, the purpose of carrying out this statistical study is to demonstrate whether clusters can be identified based on the words used by customers in the titles of the comments. To the extent that good results are obtained, the objective pursued is validated. In this case, future research should seek the best statistical methods and techniques to classify customers according to their words. Table 2 shows the results obtained in the Chi-square test between the members of each of the clusters, and the rating assigned by the users was 565.475, with a significance level of 0.000.

Table 2. Cluster analysis of rating.

Cluster		**Rating**					**Total**
		1	**2**	**3**	**4**	**5**	
1	Frequency	15	30	61	239	253	598
	% File	2.5%	5.0%	10.2%	40.0%	42.3%	100.0%
2	Frequency	15	37	77	308	163	600
	% File	2.5%	6.2%	12.8%	51.3%	27.2%	100.0%
3	Frequency	40	34	40	11	4	129
	% File	31.0%	26.4%	31.0%	8.5%	3.1%	100.0%
4	Frequency	30	41	137	244	165	617
	% File	4.9%	6.6%	22.2%	39.5%	26.7%	100.0%
5	Frequency	412	374	851	1096	601	3334
	% File	12.4%	11.2%	25.5%	32.9%	18.0%	100.0%
Total	Total	512	516	1166	1898	1186	5278
	% Total file	9.7%	9.8%	22.1%	36.0%	22.5%	100.0%

Pearson Chi-squared: 565.475. df: 16. Significance: 0.000.

Table 2 shows that the users who tend to give a good rating to the airline were assigned to Cluster 1, given that the rating of 4 includes 40.0% of the customers and the rating of 5 includes 42.3%. Therefore, the customers classified in this cluster have a high rating of the airline's service. Cluster 2 is similar to Cluster 1, but with the difference that half of the users give a rating of 4 (51.3%), followed by a rating 5 (27.2%). Further analysis will examine whether there are any relevant differences between customers' words in the two clusters that are generally satisfied with the airline.

On the one hand, Cluster 3 classifies customers who give a lower rating to the services offered by the airline. In rating 1, 31.0% of customers are found, in rating 2, 26.4%, and in rating 3, 31.0%. Hence, it is clear that the most dissatisfied customers tend to share a common vocabulary to rate the service they have received. On the other hand, Cluster 4 obtains a distribution of percentages similar to the total average, except in ratings 1 (4.9%) and 2 (6.6%), where the allocation of customers is significantly lower than the total average. Finally, Cluster 5 is the largest, with 3334 cases, which shows a tendency toward medium or low ratings of the service received, with half of the assigned clients concentrated in ratings 1, 2, and 3.

Appendix C shows the results obtained in the clusters identified according to the significant labels. The number of times each label appears in the titles of the comments is shown. Thus, it is possible to determine the words that most identify the users assigned to each cluster. In Cluster 1, the most frequently used tag is travel (362), followed by excellent (260). Other labels that also identify this group of clients are punctual (31), comfortable (24), not (16), always (15), calm (14), pleasant (12), normal (12), more (12), but (11), experience (10), and pleasure (10). The excellent label matches the positive ratings of this cluster, which is associated with the travel tag. Other adjectives used to rate the airline positively are punctual, comfortable, quiet, pleasant, experience, or pleasure. In contrast, a label that can be considered negative is no, which is usually used a large number of times, and, in this cluster, only appears 16 times.

The labels that appear most in Cluster 2 are flight (88), punctual (70), good (65), travel (54), experience (38), comfortable (27), not (21), and but (20). These are generally positive tags, especially related to flight punctuality. However, some clients use the words not and but, which are typically used to make a negative remark or detract from some positive attribute. These results are related to the great concentration in the value 4 rating in this cluster. In contrast, in Cluster 3, the most frequently used labels are worse (77) and space (53), with fewer labels assigned. This result means that the customers assigned to this cluster are unhappy with the poor performance of different airline services, but especially with the space between the seats.

Cluster 4 groups clients who use varied and generally positive language. The most commonly used labels are excellent (50), punctual (49), calm (30), normal (30), and pleasant (25), which are, in general, positive adjectives. However, labels are also used that negatively rate the airline's service, such as delayed (23) and uncomfortable (12), in contrast to other positive qualifiers such as perfect (18) and comfortable (18). Therefore, these customers are generally satisfied, but some show dissatisfaction with the plane's delays and discomfort. Cluster 5, the most numerous, is the one with the most extensive variety of labels to express customers' qualitative ratings. The labels used most are no (199), experience (118), more (103), comfortable (95), good (90), better (89), normal (86), delay (83), always (80), bad (60), quality (52), wait (51) and badly (50). These results show that this cluster is the worst, and defined by using varied qualifiers and with the opposite sense. Another visual description of the cluster analysis on the identified labels is displayed in Table 3 to provide airlines with proper managerial solutions and recommendations based on interpretation in Appendix C.

Table 3. Managerial recommendation for Iberia.

IBERIA	Group1 (The quality of service–inflight experience) In general, there is an excellence satisfaction level with Iberia' services in the reviews, however the company needs to redouble its efforts to improve the in-flight entertainment experience for passengers. Group2 (The quality of service–flight punctuality) Iberia accomplished good results when it comes to punctuality of flight Group3 (Comfort of seats) The key labels are (worse and space). Managers have to pay more attention to passenger seat space, design and comfort in order to reduce customer dissatisfaction on the mentioned topic Group4 (Flight problems: delays, cancellations, reschedule, and overbooking) Passenger satisfaction with Iberia' service is at a good level, but the negative reviews are about delay. It is recommended that managers take decisions regarding the time of procedures such as check-in before flight. Group5 (The quality of service, check-in and boarding, baggage delivering, personnel service) Most of the negative reviews are about bad quality of service, delays to check-in baggage, and the attitude of the crew staff, which should be re-evaluated. Managers can identify the cause of passenger dissatisfaction with Iberia staff service and training new customer communication to meet up with their needs before and during the flight (check-in, boarding and handling service).

5. Discussion of Results

Based on the research carried out, it is clear that the proposed methodology for designing a learning machine model that detects the key tags in the titles of customers' online comments is validated. Moreover, it is a methodology that has a learning process, only requiring specific updates to improve the tags that make up the database to analyze the contents of the users' online comments. The initial process of data capture is the previous step to carrying out the statistical analyses. The first step was the descriptive analysis, which verified that the comparison of the linguistic sense of the labels with the averages of the ratings of the titles of the comments where they appear was logical. Thus, the labels that show positive aspects of the airline tend to obtain high scores around the value of 4, whereas the negative labels orient the averages towards low values between 1 and 2.

Another fundamental aspect of the descriptive analysis is establishing the number of times a label appears in the comments. These data are essential for designing and debugging a label database for content analysis. When tags appear only a few times, for example, 1 or 2 times, it is not possible to validate the relationship between the tag and the average of the ratings obtained. Moreover, it is possible that if the label is complemented by others that may change its meaning, such as a negation, it may give an average that does not correspond to the logic of the label when reading it in isolation. This is the case of good or not good, where the meaning of the label without the context has a specific orientation, but when linked to another label, its meaning can change diametrically. Despite these appreciations that serve as a basis for future research, the results obtained are satisfactory because the relationship between the key labels and the rating is demonstrated only by analyzing the averages obtained in the ratings and the number of times they appear in the customer reviews. Likewise, labels that do not have a significant influence on ratings are observed. The descriptive results obtained, along with the results of the regression analysis, make a fundamental contribution to the development of learning machine algorithms for detecting keywords in the content analysis of online ratings.

In this line, regression analysis confirms that the machine's approach to learning the key labels is valid. The high number of significant labels and the high adjusted square R validate the proposed methodology. It is confirmed that the linear regression provides essential information for the development of a learning machine and artificial intelligence program, given that it provides two essential data for assessing the labels: (1) the level of significance and (2) the coefficient. Together with the descriptive data of the average ratings and the number of times they appear in the titles of the comments, these data make it possible to develop an algorithm that learns continuously.

On the one hand, the significant labels are determined, but we must not forget the other labels, which, in time, can be of great interest in the constant improvement of the learning algorithm. In this study, only the labels are analyzed individually. However, in future research, the study should be combined with other key labels that can modify or consolidate the relationship between the comment title and the rating given by a customer. Another aspect to consider is that, because the participation of a specialist feeds the label database, a moment will come when the vocabulary available in the database will be so extensive that it will require only a small number of improvements. In this context, the regression is also presented as a useful tool to study the interrelations between labels that appear in the same title or comment.

In this research, a first step is taken because key labels are identified. These are qualitative variables, and they are related to a quantitative variable of maximum strategic interest, such as the airline's global assessment and its service. Moreover, a means of assessing the labels is discovered that is scientifically tested through descriptive and multiple regression analysis. The results obtained confirm that, as expected, there is a logical relationship between the words used to evaluate a specific service, company, or brand and a variable that measures the perception or attitude, depending on the degree of interaction between the passenger and the airline rating measured in TripAdvisor. Moreover, in this type of variable, this logic has a positive or negative sign and an intensity, depending on the coefficient obtained.

Regarding the cluster analysis carried out, even though some of its results are not conclusive, it can be considered an exploratory study of interest for future research. First, four clusters of clients were identified who use similar words to evaluate their online opinions. From this perspective, the analysis demonstrated that the type of label can be used to categorize customers. Regarding Cluster 5, it was the worst defined, given that almost half of the users were assigned to it. Nevertheless, this result does not disqualify this study because it shows that it is an exciting and fruitful field of study where the classification of customers must advance, not only by using different techniques, but also by improving the process of dividing and, if necessary, subdividing the clusters created.

Likewise, it would be interesting to use other types of classificatory variables, if possible, such as age, social class, nationality, and level of study, if they contribute to clarifying the characteristics of the typologies defined. From the results obtained, it can be stated that the methodology for preparing labels and determining which ones are significant in the general rating is satisfactory for carrying out a classification of customers. Along these lines, depending on the information stored in the databases and processed with the appropriate statistical methods, it will be possible to pre-classify some of the users according to the type of vocabulary they use to express their opinions on the Internet.

The results of this process has been the understanding and identification of clusters with keywords that are similar to each other in terms of content and unlike other clusters. Moreover, comparing the results of this study with previous research which has defined key labels and topics extracted from online reviews of airlines (34,56,94,97,99) has shown similarities in terms of the key labels identified upon modeling algorithms process in identifying repetitive labels in the reviews. However, our findings demonstrate that using cluster analysis can be identified based on the words used by passengers in the title of comments. In addition, they show the most important aspects of services identified by the passengers assigned to each cluster group rating of Iberia, and the main aspects is about (1) quality of customer service which refers to the important of the performance of this service, (2) inflight experience, (3) punctuality of flight, (4) flight delays, (5) check-in, (6) personnel service. Research from Masorgo et al. [102] using expectancy disconfirmation theory EDT, they found that both arrival delays and involuntary denied boarding negatively affect customer satisfaction, their results show the importance of managing passenger expectation about airline service and the inflight experience.

Finally, an essential aspect of implementing this type of methodology to develop learning machines and artificial intelligence in content analysis is the way the label databases are constructed. As the proposed model shows, this has to be a continuous process where information is transferred from the Internet and a specialist to the software developed for this purpose. Two alternatives have been proposed in the study. One is to create the database based on the different words that appear in the comments' titles without additional processing. The other alternative is to establish the roots of the words used in order to reduce the number of labels without losing the meaning of the words. In this case, the software was created to generate and identify the roots of the words with six or more characters. The results showed that many of these types of labels have a significant relationship with the general rating, and the descriptive analysis contributed to clarifying the meaning and intensity of the labels.

Several contrasting programs have already been used to simplify the words according to their English root, but not in Spanish. Thus, it was necessary to develop and implement specific software to apply to the Spanish comments about Iberia airline. Despite obtaining satisfactory results, the program can be improved, for example, by grouping the conjugations of irregular verbs within the same basic label. We create a variable that is the reference for that tag when the database is created. For example, the past tense of the verb to go is went, which cannot be related because they share a minimum number of familiar characters. For these cases, a variable could be added where the base label is assigned. It would also be interesting to determine when the system creates acts autonomously without consulting a specialist. In this context, a periodic validation should be carried out of whether its processes and forecasts align with reality.

6. Conclusions

This study's main conclusion is that content analysis of online customer opinions can be transformed into dichotomous variables (0, 1) and then related to a quantitative variable such as the overall rating. Through this methodology, coefficients and signs of the labels are obtained that facilitate their interpretation by a learning machine or artificial intelligence. In this context, the vocabulary people use tends to vary over time, as well as the assessment given to each word. Therefore, the results obtained in this study are of great interest for developing this line of research because they offer methodological support for giving a quantitative value to the labels.

The creation of the label database is an essential aspect of carrying out this type of study. It requires the development of specific software to solve the problems that arise in the language. In this context, the study demonstrated that a tag database based on the root of the words obtains satisfactory results and simplifies these types of studies and algorithms. In this regard, alternatives that could improve the learning machine for future research were observed, such as the insertion of irregular verbs and simple word structures, which would make it possible to better predict the meaning and intensity of the customers' opinions.

Based on the two aspects mentioned above, a learning machine structure is designed that, at first, obtains information from a specialized person, but as its knowledge increases, can become autonomous. In this context, utilizing descriptive statistical analysis and multiple regressions, it starts an internal process of permanent learning that can be the basis for developing an artificial intelligence designed to manage the strategic aspect of online relationships with customers. The linear regression offers two fundamental data to build a continuous learning algorithm, that is, the sign of each label's relationship with the general rating and the intensity measured by the coefficient obtained. This analysis must complement the descriptive analysis, where the frequency with which the words are used is a key factor in the evaluation of the words and their relationship with the average rating obtained in the comments where each label appears.

The results obtained in the multiple linear regression show that a high adjusted R square is achieved, demonstrating that the logic of language can be translated into quantitative terms related to customers' online opinions. Moreover, the regression provides essential information for developing a learning machine and artificial intelligence in the language used in online user feedback. In this context, the study demonstrates the great importance of having a sign of a relationship regarding a quantitative variable that values customers' perceptions or attitudes toward a brand or service. Likewise, each label's coefficient is a measure of intensity of the general rating, which makes it an essential element in assessing customer interactions. From this perspective, the linear regimen offers more information than neural networks, where the key labels, their sign, and their intensity cannot be determined.

The limitations of this study provide opportunities for carrying out future research and improvements in this field. On the one hand, the need to improve the algorithm to find the roots of words to simplify the learning process in languages other than English has already been mentioned. This process should be as automated as possible, so that a specialist's involvement is concentrated in the earliest stages of learning. Furthermore, the joint analysis of descriptive and multiple regression results needs to be improved. Thus, the frequency of use of words should be taken into account, so that the coefficients and signs that are statistically assigned are not biased. A minimum level of frequency needs to be established to validate the results obtained.

Regarding the cluster analysis, the results indicated that exploratory research shows an exciting future for this type of investigation. Along these lines, it might be possible to define clients' profiles with greater precision by taking other variables into account such as flight class (first class, business class, economy class) [53], culture dimensions [93], domestic and international flights [93], geographical regions [98], low cost and full service carriers [99], using different platforms to gather information such as Twitter [103], mobile app [92], and SKYTRAX [94,98]. This research can be incorporated in more airlines in Europe and can provide comparative investigation between airlines. It is also necessary to validate the proposed methodology over time, especially in forecasting the rating evaluation when a customer gives an opinion and the typology to which s/he is most likely to belong. This methodology can be apply in multiple fields like hotels, hospitals and google play store.

In conclusion, we must emphasize the importance of having a reference variable that allows us to evaluate the meaning and intensity of the words in online reviews. In this case, we have used TripAdvisor's general rating, but other variables can be used to facilitate deciphering how customers think and what they value when they comment on a company, brand, or service. Regarding the competitive market of airlines and their various services, this study can be considered as a guide for airlines that need to keep up their positioning in the market by developing marketing strategies that attract new passengers and increase their online reputation. The results of this research give business insights implications and recommendations for predicting passenger satisfaction by analyzing online reviews in the titles. Along these lines, the possibility of merging quantitative and qualitative customer assessments as two sides of the same coin is essential for developing learning algorithms and artificial intelligence that can help employees to manage companies more competitively. The contribution of this investigation correlates to the evolution of a new approach to spot the strengths and weakness of airline' services depending on the identified key labels in order to help managers to improve passenger experience.

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Appendix A

Table A1. Descriptive analysis of labels.

Label	Number	Mean	Label	Number	Mean	Label	Number	Mean
ideal	3	5	bus	94	3.61	assistance	3	3
pleasure	12	4.75	turbulence	5	3.6	height	3	3
notable	4	4.75	lots	20	3.6	seat	137	2.99
printing	4	4.75	according	5	3.6	time	48	2.98
magnificent	14	4.71	resolved	5	3.6	regular	39	2.97
fantastic	10	4.7	queue	5	3.6	nothing	50	2.96
marvelous	10	4.7	assistant	5	3.6	individual	20	2.95
practical	3	4.67	acceptable	25	3.6	port	21	2.95
defraud	3	4.67	on board	19	3.58	plaza	133	2.95
focus	3	4.67	whole	7	3.57	pain	20	2.9
excellent	327	4.64	rest	7	3.57	average	9	2.89
latest	5	4.6	vacation	16	3.56	checking	8	2.88
impeccable	59	4.58	crew	86	3.56	educate	7	2.86
flawless	15	4.53	quite	32	3.56	where	7	2.86
exceptional	18	4.5	age	11	3.55	bathroom	7	2.86
phenomenal	6	4.5	air	19	3.53	down	7	2.86
chair	4	4.5	service	458	3.52	total	13	2.85
fan	14	4.43	touch	4	3.5	then	13	2.85
unbeatable	5	4.4	topic	8	3.5	case	13	2.85
agreed	5	4.4	seriousness	4	3.5	airport	20	2.85
have	3	4.33	feel	4	3.5	web	6	2.83
pass	3	4.33	route	4	3.5	repeat	6	2.83
modern	12	4.33	point	12	3.5	half	6	2.83
entertaining	3	4.33	lend	8	3.5	less	12	2.83

Table A1. *Cont.*

Label	Number	Mean	Label	Number	Mean	Label	Number	Mean
effective	3	4.33	order	6	3.5	cheap	6	2.83
appreciate	3	4.33	menu	6	3.5	attention	11	2.82
chord	3	4.33	frequent	10	3.5	straits	11	2.82
pleasurable	23	4.3	replicate	4	3.5	narrow	17	2.82
TRUE	4	4.25	although	18	3.5	go	5	2.8
serviceable	4	4.25	aspect	4	3.5	arrive	5	2.8
sensation	4	4.25	current	8	3.5	uncomfortable	54	2.76
even	4	4.25	cabin	21	3.48	value	4	2.75
like	8	4.25	deal	86	3.47	sun	44	2.75
favor	4	4.25	food	72	3.47	follow	4	2.75
astonishing	4	4.25	something	13	3.46	manner	4	2.75
cross	4	4.25	airline	138	3.46	mother	4	2.75
home	18	4.22	minute	9	3.44	low-cost	4	2.75
cute	5	4.2	without	250	3.43	justify	4	2.75
cordial	11	4.18	entre	56	3.43	thanks	4	2.75
leap	6	4.17	swindle	12	3.42	works	8	2.75
drinks	6	4.17	price	91	3.42	tough	4	2.75
fast	32	4.16	lines	12	3.42	passenger	23	2.74
punctual	468	4.15	connection	19	3.42	reenter	11	2.73
professional	22	4.14	job	5	3.4	old	22	2.73
efficiency	7	4.14	also	5	3.4	after	140	2.73
tourist	18	4.11	gate	5	3.4	date	7	2.71
trading	9	4.11	routine	5	3.4	enough	3	2.67
careful	19	4.11	legs	15	3.4	appear	9	2.67
nice	100	4.11	request	5	3.4	palm	3	2.67
relation	22	4.09	need	5	3.4	or	3	2.67
great	52	4.08	row	5	3.4	check in	3	2.67
quiet	59	4.07	escape	5	3.4	control	3	2.67
class	34	4.06	subsequent to	5	3.4	tariff	3	2.67
always	114	4.05	inside	15	3.4	fault	3	2.67
quality	80	4.04	return	51	3.39	high	38	2.66
summer	3	4	mess	16	3.38	already	33	2.64
last	7	4	amazing	8	3.38	bad	381	2.64
journey	14	4	during	8	3.38	desire	8	2.63
usually	8	4	detail	8	3.38	delay	103	2.61
startles	4	4	but	170	3.37	between	5	2.6
simply	5	4	period	11	3.36	dice	20	2.6
sure	16	4	all	11	3.36	ok	19	2.58
relaxed	5	4	bread	22	3.36	side	19	2.53
regional	6	4	on	20	3.35	hours	56	2.52
reasonable	6	4	much	52	3.35	respect	6	2.5

Table A1. *Cont.*

Label	Number	Mean	Label	Number	Mean	Label	Number	Mean
promotion	3	4	highlight	3	3.33	slow	4	2.5
predicted	4	4	put	3	3.33	can	6	2.5
prefer	3	4	power	6	3.33	equal	4	2.5
Fare-quality	3	4	couple	3	3.33	constant	4	2.5
pilot	8	4	inconvenient	6	3.33	behavior	4	2.5
film	4	4	provision	6	3.33	see	63	2.41
displays	4	4	different	3	3.33	lack	29	2.41
opinion	6	4	portion	6	3.33	responsibility	5	2.4
require	3	4	whatever	3	3.33	operated	5	2.4
Christmas	3	4	which	6	3.33	operate	10	2.4
deserves	5	4	short	9	3.33	crummy	5	2.4
pet	3	4	face	24	3.33	loose	5	2.4
praise	3	4	mouth	3	3.33	close	5	2.4
language	3	4	alike	117	3.32	change	5	2.4
big	4	4	yet	28	3.32	why	8	2.38
fleet	5	4	some	19	3.32	baggage	52	2.38
easy	5	4	small	10	3.3	badly	82	2.38
excellence	4	4	bridge	14	3.29	common	8	2.38
spectacular	5	4	delicious	18	3.28	zero	8	2.38
charm	3	4	neither	248	3.28	world	14	2.36
in time	10	4	never	22	3.27	scammed	3	2.33
say	4	4	offer	65	3.26	sir	3	2.33
price-quality	5	4	flag	19	3.26	remains	9	2.33
cabotage	3	4	only	8	3.25	priority	3	2.33
help	3	4	transport	4	3.25	predisposition	3	2.33
friendly	27	4	system	4	3.25	minimum	3	2.33
bueno	108	3.96	availability	4	3.25	mini	6	2.33
very	605	3.95	cutout	4	3.25	Information	15	2.33
comfort	39	3.95	post	4	3.25	difficulty	3	2.33
incidence	16	3.94	possibility	4	3.25	pause	9	2.33
general	30	3.93	position	4	3.25	deficient	6	2.33
fly	39	3.92	conventional	8	3.25	review	3	2.33
food	183	3.92	latinoamerica	4	3.25	obtain	3	2.33
ate	11	3.91	delete	4	3.25	fare	4	2.25
business	55	3.91	depends	8	3.25	let	4	2.25
duration	41	3.9	basic	4	3.25	care	16	2.25
international	10	3.9	acompaña	4	3.25	check-in	4	2.25
end	19	3.89	give	25	3.24	luggage	51	2.24
proposal	8	3.88	if	791	3.22	util	5	2.2
reach	8	3.88	land	14	3.21	dirty	10	2.2
concerning	7	3.86	none	24	3.21	inexpensive	5	2.2

Table A1. *Cont.*

Label	Number	Mean	Label	Number	Mean	Label	Number	Mean
Mexico	14	3.86	difference	14	3.21	fatal	5	2.2
setback	7	3.86	withdraw	5	3.2	guilt	5	2.2
right	75	3.85	revisit	5	3.2	ancient	10	2.2
luck	6	3.83	recommend	5	3.2	reservation	17	2.18
preferential	6	3.83	normal	138	3.2	contribute	17	2.18
moment	6	3.83	final	5	3.2	cancelation	6	2.17
intercontinental	6	3.83	additional	5	3.2	attitude	6	2.17
factor	6	3.83	rule	140	3.19	leave	19	2.16
traverse	6	3.83	more	192	3.19	employee	7	2.14
thing	6	3.83	space	78	3.18	suitcase	8	2.13
premium	11	3.82	responsible	6	3.17	organization	10	2.1
expectations	11	3.82	to get better	48	3.17	possible	15	2.07
surprise	26	3.81	special	12	3.17	attention	14	2.07
direct	27	3.81	choice	6	3.17	client	51	2.06
degrade	5	3.8	foot	32	3.16	reply	3	2
incidents	5	3.8	stewardess	20	3.15	page	3	2
reliable	10	3.8	life	21	3.14	online	8	2
executive	5	3.8	medium	22	3.14	kids	4	2
effectiveness	5	3.8	unexceptional	7	3.14	hands	5	2
classic	5	3.8	low	28	3.14	subsequently	4	2
when	9	3.78	go after	16	3.13	unpunctual	4	2
since	26	3.77	corporation	8	3.13	impossible	14	2
flight	817	3.75	scarce	9	3.11	grade	3	2
pears	4	3.75	standard	10	3.1	exists	8	2
place	4	3.75	no	711	3.1	gave	11	2
plenty	4	3.75	economic	10	3.1	charge	8	2
such	333	3.75	from	103	3.1	ticket	11	2
long	46	3.74	before	39	3.1	water	7	2
holiday	45	3.73	expensive	22	3.09	exhaust	3	2
weight	11	3.73	same	12	3.08	disappointment	22	1.91
new	22	3.73	airplane	133	3.08	sardines	7	1.86
a lot	26	3.73	by	163	3.06	poor	7	1.86
warranty	11	3.73	towering	17	3.06	plus	5	1.8
comfortable	160	3.73	pay	21	3.05	left	5	1.8
option	39	3.72	express	26	3.04	advertising	4	1.75
and	1414	3.71	boarding	26	3.04	higher	4	1.75
transatlantic	7	3.71	form	30	3.03	cheated	4	1.75
clothes	42	3.71	wifi	4	3	buy	4	1.75
interests	7	3.71	tv	4	3	infant	4	1.75
going	654	3.71	crossing	3	3	regrettable	15	1.73
better	273	3.7	transoceanic	6	3	glass	3	1.67

Table A1. *Cont.*

Label	Number	Mean	Label	Number	Mean	Label	Number	Mean
attention	318	3.69	contact	3	3	still	3	1.67
vip	3	3.67	pulling	3	3	probable	3	1.67
satisfied	3	3.67	type	4	3	hair	6	1.67
except	6	3.67	persons	5	3	overbooking	9	1.67
peace	6	3.67	think	3	3	horror	6	1.67
reduced	3	3.67	part	8	3	explanation	6	1.67
money	3	3.67	pay	10	3	disaster	21	1.62
background	3	3.67	gold	13	3	nightmare	5	1.6
number	3	3.67	leisure	7	3	painful	5	1.6
frequency	3	3.67	level	8	3	warn	5	1.6
defect	3	3.67	local	3	3	month	7	1.57
status	3	3.67	bring	6	3	worse	4	1.5
entertainment	24	3.67	together	4	3	pessimistic	45	1.47
select	6	3.67	irregular	3	3	error	9	1.44
cash	3	3.67	internal	4	3	human	5	1.4
destination	9	3.67	try	3	3	shame	8	1.38
must	3	3.67	until	9	3	terrible	6	1.33
costa	3	3.67	gentle	9	3	prepotent	3	1.33
puddle	3	3.67	cold	4	3	inexistent	3	1.33
charco	3	3.67	stay	3	3	non-compliance	3	1.33
coast	15	3.67	scale	17	3	void	3	1.33
thank	3	3.67	link	3	3	abuse	3	1.33
problem	64	3.66	efficient	9	3	mistreatment	4	1.25
motto	65	3.66	lag	3	3	fraud	24	1.08
experience	182	3.66	mean	3	3	thrown away	3	1
departure	23	3.65	cost	6	3	fright	4	1
company	146	3.65	catering	6	3	motive	3	1
extra	11	3.64	pricey	3	3	unpresentable	5	1
able to	8	3.63	fits	4	3	avoidance	3	1
organized	8	3.63	transportation	3	3	chaos	4	1
habitual	8	3.63	respite	3	3	app	3	1

Appendix B

Table A2. Regression analysis with rating as independent variable (r2 adjusted 0.546).

Variables	Beta	T	Sig.	Variables	Beta	T	Sig.
(constant)	3.739	131.628	0.000 ***	space	−0.535	−3.909	0.000 ***
seat	3.864	2.236	0.025 *	reservation	−0.562	−1.971	0.049 *
keep	3.770	2.203	0.028 *	never	−0.576	−2.670	0.008 **
additional	3.539	4.028	0.000 ***	client	−0.607	−4.016	0.000 ***

Table A2. *Cont.*

Variables	Beta	T	Sig.	Variables	Beta	T	Sig.
tower	3.289	2.441	0.015 *	if	−0.617	−3.144	0.002 **
deliver	3.276	3.383	0.001 **	nothing	−0.628	−3.114	0.002 **
husband	3.113	2.954	0.003 **	charge	−0.637	−1.942	0.052
add up	3.101	3.124	0.002 **	lost	−0.672	−3.295	0.001 **
then	3.015	2.209	0.027 *	improved	−0.698	−3.258	0.001 **
distribution	2.925	3.409	0.001 **	pain	−0.721	−2.992	0.003 **
slow	2.893	2.164	0.031 *	baggage	−0.769	−4.237	0.000 ***
forecast	2.883	4.608	0.000 ***	all	−0.772	−2.229	0.026 *
restrict	2.860	2.199	0.028 *	regular	−0.779	−5.014	0.000 ***
agency	2.836	2.792	0.005 **	disgust	−0.786	−2.134	0.033 *
gender	2.597	2.151	0.032 *	stewardess	−0.788	−2.854	0.004 **
congratulations	2.537	2.646	0.008 **	level	−0.813	−2.312	0.021 *
whole	2.524	2.313	0.021 *	impossible	−0.818	−2.896	0.004 **
find	2.490	2.830	0.005 **	until	−0.821	−2.332	0.020 *
natural	2.355	2.439	0.015 *	no	−0.840	−10.688	0.000 ***
alien	2.305	2.353	0.019 *	absolute	−0.840	−2.254	0.024 *
centimeter	2.220	2.184	0.029 *	high	−0.854	−2.307	0.021 *
affair	2.169	1.714	0.087	horror	−0.900	−3.355	0.001 **
evident	2.153	1.733	0.083	give	−0.902	−1.834	0.067
barbarian	2.116	3.508	0.000 ***	vary	−0.904	−2.377	0.017 *
fan	2.101	2.336	0.020 *	delay	−0.907	−8.222	0.000 ***
tracks	2.088	2.334	0.020 *	lack	−0.930	−4.430	0.000 ***
price	2.058	2.797	0.005 **	uncomfortable	−0.965	−8.257	0.000 ***
number	2.015	1.835	0.067	drinks	−0.969	−1.792	0.073
beverage	1.943	1.644	0.100	organization	−1.017	−2.909	0.004 **
mistake	1.929	2.557	0.011 *	buy	−1.023	−3.820	0.000 ***
light	1.915	1.800	0.072	quality	−1.054	−1.868	0.062
indecent	1.890	2.025	0.043 *	think	−1.064	−2.778	0.005 **
documentation	1.871	1.978	0.048 *	solve	−1.137	−2.168	0.030 *
curious	1.854	1.647	0.100	communicate	−1.150	−2.322	0.020 *
defraud	1.837	2.169	0.030 *	lowcost	−1.171	−2.709	0.007 **
electronic	1.801	1.823	0.068	old	−1.175	−3.894	0.000 ***
royal	1.728	1.721	0.085	warn	−1.196	−2.797	0.005 **
little bit	1.709	1.901	0.057	complicate	−1.197	−1.892	0.059
place	1.696	2.515	0.012 *	delay	−1.221	−3.458	0.001 **
instructions	1.686	1.857	0.063	appear	−1.224	−3.328	0.001 **
mini	1.682	1.804	0.071	badly	−1.230	−10.679	0.000 ***
talk	1.572	1.699	0.089	telephone	−1.260	−1.909	0.056
relax	1.543	1.765	0.078	plus	−1.274	−3.039	0.002 **
personalized	1.512	1.819	0.069	pause	−1.279	−2.886	0.004 **
remedy	1.472	1.797	0.072	chaotic	−1.289	−2.462	0.014 *

Table A2. *Cont.*

Variables	Beta	T	Sig.	Variables	Beta	T	Sig.
round	1.454	1.709	0.087	terrible	−1.328	−3.483	0.001 **
road	1.426	1.723	0.085	arrival	−1.356	−2.069	0.039 *
agile	1.411	1.689	0.091	want	−1.375	−2.049	0.041 *
warm	1.382	2.501	0.012 *	bad	−1.416	−12.093	0.000 ***
have	1.340	2.554	0.011 *	unpunctual	−1.419	−2.685	0.007 **
touch	1.329	2.053	0.040 *	error	−1.441	−2.594	0.010 *
after	1.316	2.102	0.036 *	discriminate	−1.453	−2.354	0.019 *
easy	1.300	1.651	0.099	thrown away	−1.489	−2.316	0.021 *
agree	1.270	1.979	0.048 *	mistreatment	−1.507	−3.214	0.001 **
opera	1.243	2.014	0.044 *	possibility	−1.523	−2.293	0.022 *
system	1.239	1.947	0.052	water	−1.539	−2.468	0.014 *
luxury	1.184	2.006	0.045 *	ticket	−1.540	−2.787	0.005 **
magical	1.180	1.995	0.046*	forget	−1.556	−3.268	0.001 **
web	1.179	1.938	0.053	negligent	−1.577	−1.708	0.088
meeting	1.167	1.974	0.048 *	wide	−1.582	−1.831	0.067
maximum	1.151	1.986	0.047 *	avoidance	−1.583	−3.286	0.001 **
moment	1.137	2.607	0.009 **	any	−1.590	−2.322	0.020 *
unforgettable	1.128	1.943	0.052	sell	−1.600	−3.438	0.001 **
behavior	1.112	1.956	0.051	sardines	−1.620	−2.960	0.003 **
predisposition	1.040	2.064	0.039 *	down	−1.623	−2.590	0.010 *
remove	1.024	1.730	0.084	non-existent	−1.630	−2.659	0.008 **
remarkable	1.017	2.247	0.025 *	particular	−1.648	−2.804	0.005 **
magnificent	0.966	4.403	0.000 ***	painful	−1.659	−5.014	0.000 ***
fantastic	0.915	3.562	0.000 ***	frightening	−1.671	−3.387	0.001 **
great	0.886	3.607	0.000 ***	cheated	−1.678	−4.830	0.000 ***
brilliant	0.863	4.098	0.000 ***	poor	−1.699	−4.834	0.000 ***
extraordinary	0.856	1.688	0.092	lousy	−1.707	−5.211	0.000 ***
excellent	0.852	16.056	0.000 ***	load	−1.712	−1.929	0.054
end	0.825	1.967	0.049 *	deficient	−1.715	−4.378	0.000 ***
perfect	0.792	7.319	0.000 ***	breach	−1.739	−2.123	0.034 *
charm	0.786	3.130	0.002 **	decline	−1.739	−3.000	0.003 **
phenomenal	0.755	2.216	0.027 *	money	−1.739	−2.123	0.034 *
enjoyment	0.749	3.340	0.001 **	vulgar	−1.739	−2.123	0.034 *
compete	0.734	1.732	0.083	terror	−1.747	−4.856	0.000 ***
wonderful	0.715	2.732	0.006 **	worse	−1.755	−16.331	0.000 ***
house	0.699	2.914	0.004 **	exhausting	−1.761	−2.999	0.003 **
according	0.687	1.857	0.063	scammed	−1.772	−2.803	0.005 **
like	0.666	1.805	0.071	rate	−1.782	−3.391	0.001 **
faultless	0.642	2.905	0.004 **	win	−1.787	−2.156	0.031 *
unbeatable	0.637	1.679	0.093	sad	−1.804	−2.316	0.021 *
neither	0.622	2.259	0.024 *	countryside	−1.812	−2.167	0.030 *

Table A2. *Cont.*

Variables	Beta	T	Sig.	Variables	Beta	T	Sig.
first	0.586	2.916	0.004 **	half	−1.817	−3.345	0.001 **
big	0.585	4.086	0.000 ***	shame	−1.839	−5.330	0.000 ***
better	0.576	4.807	0.000 ***	fatal	−1.866	−4.491	0.000 ***
overcome	0.518	2.125	0.034 *	disaster	−1.867	−11.170	0.000 ***
almost	0.517	1.836	0.066	obsolete	−1.889	−3.019	0.003 **
time	0.466	2.207	0.027 *	disappointment	−1.900	−10.292	0.000 ***
passenger	0.465	1.852	0.064	reason	−1.902	−2.573	0.010 *
trust	0.325	1.639	0.101	hair	−1.925	−4.507	0.000 ***
fast	0.312	2.154	0.031 *	precarious	−1.926	−2.339	0.019 *
fly	0.279	1.798	0.072	value	−1.948	−3.679	0.000 ***
always	0.275	2.897	0.004 **	guilt	−1.965	−2.908	0.004 **
very	0.257	6.169	0.000 ***	shatter	−1.970	−2.349	0.019 *
good	0.233	3.068	0.002 **	awful	−1.996	−2.434	0.015 *
comfortable	0.232	3.131	0.002 **	regrettable	−2.010	−8.323	0.000 ***
punctual	0.219	4.381	0.000 ***	recognize	−2.028	−2.454	0.014 *
pleasant	0.217	2.254	0.024 *	abusive	−2.048	−3.740	0.000 ***
calm	0.201	1.945	0.052	pessimistic	−2.054	−18.103	0.000 ***
but	0.197	2.179	0.029 *	leave	−2.061	−3.622	0.000 ***
travel	0.139	2.799	0.005 **	cancel	−2.077	−5.267	0.000 ***
experience	0.128	1.832	0.067	impolite	−2.107	−3.168	0.002 **
flight	0.109	2.664	0.008 **	unpresentable	−2.127	−5.469	0.000 ***
and	0.080	1.622	0.105	bored	−2.135	−2.600	0.009 **
more	−0.177	−1.827	0.068	distorted	−2.136	−3.639	0.000 ***
wait	−0.262	−2.073	0.038 *	transfer	−2.201	−2.591	0.010 *
man	−0.337	−1.932	0.053	abandonment	−2.221	−3.796	0.000 ***
respect	−0.453	−1.751	0.080	spoil	−2.227	−1.661	0.097
low	−0.489	−1.617	0.106	filth	−2.265	−2.136	0.033 *
clean	−0.518	−1.699	0.089	inoperative	−2.266	−1.929	0.054
scarce	−0.588	−2.151	0.032 *	zero	−2.266	−5.012	0.000 ***
return	−0.594	−1.908	0.056	abuse	−2.273	−3.380	0.001 **
yet	−0.602	−1.625	0.104	date	−2.281	−1.810	0.070
cheap	−0.608	−2.077	0.038 *	antihuman	−2.285	−2.283	0.022 *
mediocre	−0.673	−1.892	0.059	reschedule	−2.316	−3.772	0.000 ***
consider	−0.713	−1.927	0.054	anger	−2.324	−2.795	0.005 **
fair	−0.748	−1.613	0.107	overbooking	−2.335	−6.042	0.000 ***
dirty	−0.751	−1.627	0.104	terminal	−2.344	−1.931	0.054
disorganize	−0.808	−2.339	0.019 *	fraud	−2.346	−12.124	0.000 ***
operated	−0.847	−1.652	0.099	meters	−2.352	−1.819	0.069
explanation	−0.861	−2.137	0.033 *	strict	−2.397	−2.558	0.011 *
standard	−0.875	−1.836	0.066	apparatus	−2.434	−2.016	0.044 *
cargo	−0.885	−2.057	0.040 *	uncomfortable	−2.440	−2.901	0.004 **

Table A2. *Cont.*

Variables	Beta	T	Sig.	Variables	Beta	T	Sig.
loose	−0.929	−1.898	0.058	general	−2.446	−2.006	0.045 *
response	−0.939	−1.654	0.098	doing	−2.461	−3.936	0.000 ***
adapt	−1.007	−1.684	0.092	lies	−2.474	−4.229	0.000 ***
fault	−1.082	−2.224	0.026 *	divide	−2.503	−2.712	0.007 **
damage	−1.100	−1.786	0.074	dire	−2.594	−7.687	0.000 ***
ignore	−1.222	−2.448	0.014 *	delete	−2.640	−2.762	0.006 **
app	−1.232	−1.770	0.077	unhuman	−2.641	−3.749	0.000 ***
word	−1.252	−1.857	0.063	run away	−2.694	−3.247	0.001 **
remember	−1.268	−2.114	0.035 *	oversold	−2.711	−3.279	0.001 **
satellite	−1.273	−1.856	0.063	expression	−2.712	−2.655	0.008 **
null	−1.451	−2.378	0.017 *	jinx	−2.714	−3.066	0.002 **
baby	−1.521	−2.493	0.013 *	revulsion	−2.739	−3.343	0.001 **
gain	−1.543	−1.652	0.099	tyranny	−2.739	−3.343	0.001 **
letter	−1.563	−1.707	0.088	unforgivable	−2.739	−3.343	0.001 **
clouds	−1.571	−1.829	0.067	fiasco	−2.739	−3.343	0.001 **
exorbitant	−1.588	−1.776	0.076	failure	−2.739	−3.343	0.001 **
infinite	−1.647	−1.624	0.104	queue	−2.739	−3.343	0.001 **
infimum	−1.657	−1.908	0.056	authorize	−2.739	−3.343	0.001 **
negligence	−1.696	−1.870	0.062	outrageous	−2.739	−3.343	0.001 **
request	−1.725	−1.827	0.068	authentic	−2.739	−3.343	0.001 **
suffer	−1.739	−2.123	0.034 *	xenophobic	−2.739	−3.343	0.001 **
frozen	−1.739	−2.123	0.034 *	criminals	−2.739	−3.343	0.001 **
pate	−1.739	−2.123	0.034 *	very poor	−2.739	−3.343	0.001 **
hate	−1.739	−2.123	0.034 *	garbage	−2.739	−3.343	0.001 **
riot	−1.739	−2.123	0.034 *	incompetent	−2.739	−3.343	0.001 **
mortal	−1.739	−2.123	0.034 *	misery	−2.739	−3.343	0.001 **
unsatisfied	−1.739	−2.123	0.034 *	navel	−2.749	−2.921	0.004 **
free	−1.739	−2.123	0.034 *	tremendous	−2.819	−3.434	0.001 **
go around	−1.739	−2.123	0.034 *	inefficiency	−2.819	−3.434	0.001 **
perfume	−1.739	−2.123	0.034 *	court	−2.865	−3.097	0.002 **
penalize	−1.739	−2.123	0.034 *	chaos	−2.920	−5.315	0.000 ***
owners	−1.739	−2.123	0.034 *	horny	−2.927	−3.020	0.003 **
unconcern	−1.757	−1.910	0.056	true	−2.935	−3.561	0.000 ***
go down	−1.766	−2.086	0.037 *	scam	−2.950	−5.937	0.000 ***
truck	−1.787	−2.156	0.031 *	default	−2.950	−2.156	0.031 *
ancient	−1.794	−2.106	0.035 *	delight	−2.954	−2.121	0.034 *
fed up	−1.795	−2.022	0.043 *	award	−2.992	−2.821	0.005 **
regret	−1.816	−2.030	0.042 *	still	−3.023	−1.891	0.059
waste	−1.832	−2.217	0.027 *	rue	−3.080	−2.879	0.004 **
stumbling	−1.848	−2.254	0.024 *	delicacy	−3.081	−2.310	0.021 *
liquor	−1.869	−1.883	0.060	juice	−3.139	−2.070	0.039 *

Table A2. *Cont.*

Variables	Beta	T	Sig.	Variables	Beta	T	Sig.
refrain	−1.878	−2.289	0.022 *	secondary	−3.204	−3.739	0.000 ***
divert	−1.891	−2.208	0.027 *	frustration	−3.221	−3.751	0.000 ***
canned	−1.891	−1.632	0.103	car	−3.311	−4.019	0.000 ***
admit	−1.899	−2.309	0.021 *	botched	−3.324	−3.998	0.000 ***
believe	−1.899	−2.309	0.021 *	rude	−3.409	−2.890	0.004 **
see	−1.907	−1.840	0.066	converted	−3.437	−3.138	0.002 **
useless	−1.943	−2.180	0.029 *	confusion	−3.636	−3.052	0.002 **
functional	−1.973	−2.235	0.025 *	permitted	−3.693	−2.905	0.004 **
remember	−1.996	−1.895	0.058	ambient	−3.708	−2.366	0.018 *
private	−2.001	−1.752	0.080	chair	−3.763	−2.713	0.007 **
turbulent	−2.072	−2.521	0.012 *	occupied	−3.826	−2.367	0.018 *
sweetie	−2.111	−2.503	0.012 *	find out	−4.170	−3.048	0.002 **
converting	−2.151	−1.910	0.056	omitted	−4.207	−2.495	0.013 *
modification	−2.177	−2.511	0.012 *	nobody	−4.425	−3.223	0.001 **
airplane	−0.285	−2.175	0.030 *	relapsing	−4.531	−3.545	0.000 ***
hours	−0.323	−2.081	0.037 *	lay off	−4.681	−2.930	0.003 **
normal	−0.532	−6.722	0.000 ***	indifferent	−5.076	−3.635	0.000 ***

Significance level: * $p < 0.05$; ** $p < 0.01$, *** $p < 0.001$.

Appendix C

Table A3. Cluster analysis based on labels.

Cluster 1		Cluster 4		Cluster 5 (Continuation)	
Label	**Number**	**Label**	**Number**	**Label**	**Number**
nice	12	pleasant	25	absolute	7
airplane	8	water	2	abusive	5
well	9	void	2	enjoyable	36
characteristic	9	plane	10	water	4
warm	9	warn	2	tall	6
load	2	stewardess	2	old	8
client	3	economic	3	backwardness	6
comfortable	27	well	9	plane	49
buy	3	ticket	2	warn	5
disaster	2	quality	9	stewardess	12
charm	3	trait	8	cheap	8
distance	4	cancel	9	drinks	3
exceptional	3	almost	2	good	90
excellent	260	comfortable	18	ticket	6
experience	10	buy	4	quality	52
marvelous	5	frustration	2	cancel	3
like	2	disaster	2	chaos	4

Table A3. *Cont.*

scheduled	5	attraction	2	chaotic	3
horror	2	scarce	3	Position	5
embarrassing	8	gap	5	house	15
horrible	3	remain	3	almost	9
wrong	4	awesome	4	zero	6
luggage	2	excellent	50	client	45
more	12	adventure	9	charge	13
best	6	explanation	2	comfortable	95
very	2	fantastic	6	compete	4
blank	2	date	2	buy	20
neither	2	unusual	3	communicate	4
Not	16	general	3	consider	6
normal	12	gender	3	any	3
never	3	great	6	guilt	5
accurate	3	hours	8	damage	3
but	11	pure	2	give	7
pessimistic	9	impossible	2	disappointment	20
pleasure	10	uncomfortable	12	deficient	3
first	5	unbeatable	3	defraud	5
punctual	31	regrettable	2	leave	7
fast	5	clean	2	disgust	6
standar	3	magnificent	2	disaster	28
respect	3	atrocious	7	disrupt	5
prorogation	2	bags	7	money	3
if	7	Wonderful	3	discriminate	3
always	15	larger	14	charm	6
beats	2	better	5	find	3
calm	14	nought	2	cheated	8
crew	4	neither	3	scarce	3
travel	362	no way	10	frightening	3
return	4	normal	30	wait	51
Cluster 2		operated	3	fraud	8
Label	**Number**	worse	6	amazing	5
pleasant	18	lost	6	experience	118
old	2	perfect	18	explanation	4
airplane	15	nevertheless	5	extra-ordinary	3
stewardess	6	pessimistic	4	lack	25
drinks	2	enjoyment	7	wonderful	5
good	65	first	4	fatal	5
feature	4	punctual	49	phenomenal	3
warm	4	fast	9	end	7
client	2	delayed	23	loose	3

Table A3. *Cont.*

comfortable	27	if	2	cold	3
according	3	continuously	5	general	18
deficient	3	overcome	2	gender	19
disrupt	2	pause	2	great	15
scarce	3	time	7	big	34
space	17	calm	30	relish	3
outstanding	15	personnel	5	until	6
experience	38	journey	4	hours	37
overall	9	**Cluster 5**		horror	8
sex	10	**Label**	**Number**	irreproachable	10
hours	5	want	6	impossible	9
flawless	2	fast	20	unpresentable	5
awkward	15	regular	29	unpunctual	3
shitty	17	reservation	16	mortifying	29
awful	10	respect	13	non-existent	3
rather	3	remove	3	inhuman	3
nil	3	delay	83	regrettable	12
neither	4	sardines	7	clean	9
not	21	divide	3	low cost	4
normal	9	if	30	place	3
faultless	5	always	80	pleasant	12
but	20	solve	8	abysmal	42
pessimistic	2	standard	3	badly	50
enjoyment	11	overcome	15	impolite	4
punctual	70	postponement	7	baggage	45
fast	2	fare	3	lousy	6
if	3	terrible	5	mistreatment	5
habitually	12	terror	6	wonderful	8
duration	2	weather	25	more	103
wholly	3	scam	3	maximum	4
soundless	11	thrown away	3	mediocre	8
staff	5	all	6	better	89
travel	54	quiet	20	improvable	19
fly	3	behind	4	moment	5
flight	88	crew	23	nothing	34
Cluster 3		value	4	dire	6
Label	**Number**	variar	7	ni	23
airplane	2	sell	4	level	7
comfortable	5	shame	7	no	199
disaster	2	fly	35	normal	86
scarce	3	return	6	remarkable	3

Table A3. *Cont.*

space	53	web	4	number	3
fraud	2	bad	60	never	18
experience	7	delight	13	obsolete	3
Lack	2	seat	5	forget	4
horror	3	poor	5	organization	6
impossible	3	possibility	3	overbooking	7
uncomfortable	2	first	12	appear	10
crappy	6	prompt	306	pasajero	20
mejor	2	pensar	5	hair	6
no means	4	Lost	32	Pain	16
worse	77	impeccable	39	painful	7
pero	9	however	111		
precise	4				
fast	2				
regularly	2				
trip	3				

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