TRR
JOURNAL OF THE TRANSPORTATION RESEARCH BOARD

Research Article

Transportation Research Record
1–18

DOI: 10.1177/03611981221112096
journals.sagepub.com/home/trr
SAGE

Understanding Airline Passengers during Covid-19 Outbreak to Improve Service Quality: Topic Modeling Approach to Complaints with Latent Dirichlet Allocation Algorithm

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Abstract

The COVID-19 pandemic has deeply affected the airline industry, as it has many sectors, and has created tremendous financial pressure on companies. Flight bans, new regulations, and restrictions increase consumer complaints and are emerging as a big problem for airline companies. Understanding the main reasons triggering complaints and eliminating service failures in the airline industry will be a vital strategic priority for businesses, while reviewing the dimensions of service quality during the COVID-19 pandemic provides an excellent opportunity for academic literature. In this study, 10,594 complaints against two major airlines that offer full-service and low-cost options were analyzed with the Latent Dirichlet Allocation algorithm to categorize them by essential topics. Results provide valuable information for both. Furthermore, this study fills the gap in the existing literature by proposing a decision support system to identify significant service failures through passenger complaints in the airline industry utilizing e-complaints during an unusual situation such as the COVID-19 pandemic.

Keywords

decision support system, airline industry, low-cost carrier, full-service carrier, customer complaints, text mining, latent dirichlet allocation algorithm

Intense competition in the airline industry requires successful customer relationship management, both physical and on digital platforms, to maximize potential revenues while keeping the customer satisfied. Monitoring customers' feedback and acting on the results provides a deeper multi-faceted understanding of the service provided by the business. Analyzing online feedback is seen as a low-cost and effective way to improve goods/service quality, to react to failures, and to assist e-WOM (electronic-word-of-mouth) management, which significantly affects consumers' airline choices (*1*, *2*). With the spread of digital technology, it is now easier than ever for air passengers to "punish" airlines for poor service quality through online platforms (*3*).

The airline industry has a global economic impact of \$3.5 trillion annually under normal circumstances and has lost \$1.8 trillion in the last year. The impact of the COVID-19 pandemic, which started in February 2020, with the aviation industry reaching its financial lowest point in April 2020, was the biggest shock to the air travel and aviation industry since World War II (*4*). The industry's operations largely came to a halt, with passenger traffic down 94% from the previous year (*4*, *5*).

Turkish Airlines and Pegasus Airlines, both based in Turkey, have been shown to have operated at a relatively high intensity during this period. According to EUROCONTROL's Daily Traffic Variation—Aircraft Operators (2020) report, Turkish Airlines had the highest average number of flights between March 1 and December 31, 2020, while Pegasus was ranked sixth (*6*).

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In this period, Istanbul Airport, which is used mainly by Turkish Airlines, ranked second, right after Amsterdam, and Istanbul Sabiha Gökçen Airport, which is mostly used by Pegasus Airlines, ranked fourth. Between March 1 and December 31, 2020, the initial phase of the COVID-19 outbreak, Istanbul faced a relatively busy time on the EUROCONTROL network (*7*). With a $21 billion turnover, the airline industry in Turkey carried 208 million passengers from 56 different airports located in Turkey, with 1.6 million flights in 2019 (*8*). Including airlines and their supply chains, as well as foreign tourists, the industry is estimated to generate 5.2% of total gross domestic product (GDP), which is $44.8 billion (*9*). Despite a sharp drop to 81 million passengers in 2020, the predictions show that the sector may return to the 2019 level in 2023 (*8*, *10*). In this context, it is considered essential to analyze customer complaints and identify differences between these two airlines, which have had a relatively busier period than rivals.

Furthermore, as the companies offer low-cost and full-service options, the research findings are expected to benefit the airline industry more specifically in respect of how pandemic rules have shaped it. Because of the hygiene-oriented lifestyle fashioned by the COVID-19 epidemic, passengers are faced with a scenario other than the airline traveling they are used to. Today, all airport, in-flight, and arrival services are revised to comply with pandemic guidelines, where each country has different travel regulations (*11*). For example, PCR (polymerase chain reaction) tests, travel permit documents for people aged over 65 years old, mandatory face masks, social distance, fever checks, no-contact self-check-in, automated baggage check-in, or restrictions to in-flight services such as catering, blankets, and pillows are some new regulations for flights in Turkey and most countries (*12*). Identifying the types of consumer complaints brought on by the new travel regulations and hygiene-centric lifestyle will undoubtedly make a significant contribution to improving service processes in the airline industry today and in the near future.

Literature Review

In today's competitive environment, customer satisfaction is the core concept that all firms should fulfill. In other words, attracting new customers, and increasing the market share, referred to as the *offense strategy*, is not enough to survive; firms should retain acquired customers by creating satisfaction, which is referred to as the *defense strategy* (*13*). This strategy is surely valuable in the airline industry, where fierce competition exists (*14*). Although, for the airline industry, price is the primary factor in determining customers' intention to use low-cost carriers and defense strategy seems more suitable for full-service carriers, research reveals that the second priority of customers who prefer low-cost carriers is service quality. Pan and Truong (*15*) indicate that the service quality dimension, including, for example, a clean cabin environment, comfortable seats, and onboard facilities, is the second most important factor for satisfaction and loyalty because of increasing competition in the Chinese market.

Furthermore, Pearson et al. (*16*) found that service reputation, as one of the core intangible resources, is essential in gaining a competitive advantage for low-cost and full-service carriers. According to Koklic et al. (*17*), perceived satisfaction with the airline drives consumers to purchase from the airline in the future again and recommend to others; additionally, the link between satisfaction and repurchase behavior is stronger for the low-cost customer than for the full-cost carrier. While the main differences between low-cost carriers and full-service carriers are based on price and service quality, customers who choose low-cost carriers also expect high levels of service quality for perceived satisfaction (*18*).

Image may be another critical aspect to achieve customer satisfaction and loyalty. For example, research conducted in western countries has shown that perceived service quality elements such as ticket purchase experience, flight experience, and service reliability significantly affect the image, and airline image significantly affects consumer loyalty for both passenger classes (*19*). Calisir et al. (*20*) found that service quality is a stronger determinant of satisfaction than the price for the low-cost and full-service customer; they also discovered that the image, which expresses the perception of the brand in the customer's mind, has a stronger effect on loyalty for flights from Frankfurt to Istanbul. In this respect, it should be noted that the intensity of market competition and cultural differences may have different effects on customer satisfaction and loyalty for the low-cost and full-service airline industries. Furthermore, a positive image will ensure that customer satisfaction and loyalty, both of which are vital for marketing activities, are achieved.

The key argument here is that failure to retain customers not only leads to a decrease in sales but also encourages dissatisfied customers to express their feelings to more people than do satisfied customers (*21*). As a result, this will result in loss of image. Consumer complaint behavior (CCB) is a term used in marketing literature to explain how consumers express their dissatisfaction through explicit expression. Moreover, it is seen as a powerful signal and the last chance for businesses to solve their problem to retain the customer because it will be very likely to turn a dissatisfied customer into a satisfied and loyal customer if the organization reacts appropriately (*22*, *23*). This situation is known in the literature as the service recovery paradox, which states that efficiently resolving a complaint enhances customer loyalty (*24*, *25*).

Singh (*26*) empirically defines CCB as a three-faceted phenomenon that includes voice, third party, and private actions. *Voice* is a non-action response used to communicate the consumer's feelings about a product or service straight to the manufacturer or seller during the next purchase without informing the consumer's social circle. The *private* complaint is described as the complainant encouraging their near social circle not to use the product/service by telling them about the bad experience, or the product/service no longer being used by individuals anymore. Complaining to the consumer agency, writing a letter to the local newspaper, or taking legal action against the company are considered the most unfavorable scenario called the *third party* complaint. Istanbulluoglu et al. (*27*) developed this taxonomy of CCB further and stated that new technologies such as social media allow consumers to perform multiple actions sequentially or simultaneously. In this new approach, the crucially important point is whether a complaint is visible to the company. Using third party actions as a visible method via social media or a web page may indicate the company has been unresponsive to a complaint, which may particularly damage reputation. Considering that services cause greater dissatisfaction than physical goods (*28*), identifying complaints that require immediate action is vital to eliminate goods/service failures and provide customer satisfaction in the airline industry. A review of the literature consisting of determination of service dimensions and passenger-centered analysis studies in the airline sector is shown in Table 1.

Skytrax (*43*) states that the most common top airline customer complaints are lost baggage, delayed flights, uncomfortable seats, hidden charges/costs, customer service, cabin cleanliness, refunds, booking, terms and conditions, airline meals, and change of aircraft, respectively. The Office of Aviation Consumer Protection of USA (*44*) considers customer complaints under 12 topics. These are advertising, refunds, fares, reservations/ticketing/boarding, flight problems (cancellation, delay, misconnection), customer service, baggage, disability, other (frequent flyer), oversales, discrimination, and animals. These two examples show that the topic of the complaint has both common and unique characteristics. Culture or service class may be the effects that bring about differences. For instance, power distance, uncertainty avoidance, and individualism/collectivism factors have a positive impact on the likelihood of public action by airline customers (*45*). In another piece of empirical research, Kim and Lee (*46*) show that passengers from the USA, China, Japan, and South Korea have different complaint behaviors in respect of irregular airline conditions. Furthermore, Sezgen et al. (*1*) show that the complaints differ according to the service class. For example, while low-cost airline passengers complain about extra or hidden charges, premium cabin passengers complain about old aircraft.

In the airline industry, the development of service quality dimensions for measuring the current situation and preventing failure has been extensively studied in the literature. For instance, Tsaura et al. (*41*) state that a total of 15 service quality dimensions, including safety, courtesy of attendants, the responsiveness of attendants, comfort, and cleanness of seat, are the most important ones. Chang and Yeh (*42*) suggest 15 attributes in five dimensions to measure competitive advantages: onboard comfort, airline employees, reliability of service, the convenience of service, and handling of the abnormal condition. Gilbert and Wong (*40*) developed six dimensions—reliability, assurance, responsiveness, flight patterns, facilities, employees—and customization with a 26-item questionnaire to measure airline service quality. Research also shows there are significant differences in expectations of service based on ethnicity and purpose of travel. Nonetheless, safety is seen as the most important subcriterion under the assurance heading for all passengers.

In a recent study, Leon and Martín (*32*) suggest that technical quality, consisting of in-flight and schedule quality, is more effective than functional quality, consisting of competence, the voice of the customer, interaction ease, and information quality, for determining satisfaction with airlines. Bellizzi et al. (*30*) developed a scale consisting of 31 features with an extensive, detailed literature review. General topics of these features are flight booking, check-in procedures, evaluation of the flight experience, evaluation of the experience at the arrival, boarding procedures, punctuality of departure, cabin comfort, cabin cleanliness, flight information, cabin crew, safety and security, onboard services, punctuality at the arrival, landing procedures, and luggage delivery.

Studies carried out using this concept were either created within the framework of the SERVQUAL approach or developed a new scale. Although it is crucial to determine the standard service quality for the industry, it may not be enough to identify all aspects of consumer complaints that have a dynamic structure. The key criticism of such approaches is that customers who learn from their experience and have changing expectations are quite difficult to understand with standard quality measurement (*38, 47–49*).

Korfiatis et al. (*38*) suggest a hybrid method with topic modeling from user-generated content (UGC), such as customer reviews from Tripadvisor, to measure service quality in the airline industry. This study's findings, which propose a 20-dimensional service quality measurement, show that customer dissatisfaction is caused by delays and airlines' solutions to service failures (refunds/

Table 1. Literature Review of Service Quality Dimensions and Passenger-Centered Analysis Studies in the Airline Industry

Author	Objective of study	Method	Findings
Kwon et al. (*29*)	Topic modeling of online reviews for airlines in Asia region	Latent Dirichlet Allocation.	Important issues in the flight were delay, seat, service, and meal.
Bellizzi et al. (*30*)	Quality assessment of airlines' services	Satisfaction level was measured across 31 different factors for 942 questionnaire responses.	Developed a scale consisting of 31 features with an extensive, detailed literature review.
Lucini et al. (*31*)	Using text mining to identify dimensions of airline customer satisfaction with online customer reviews	Latent Dirichlet Allocation was used to generate customer satisfaction dimensions, and a logistic regression classifier was used to predict airline recommendation.	The most critical dimensions in predicting airline recommendations are cabin personnel, onboard service, and value for money.
Leon and Martín (*32*)	Investigating airline passenger satisfaction and service quality in the US market in respect of functional and technical quality	A 23-question survey prepared using SERVQUAL and AIRQUAL scales was applied to 624 respondents in 2018. Fuzzy logic and fuzzy segmentation methods were used for analysis.	While both technical and functional quality contributes to passenger satisfaction with airlines, passengers are more satisfied with the functional quality (competence, voice of customer, interaction ease, information quality, operations) than technical quality (in-flight, schedule).
Lim and Lee (*33*)	Service quality perceptions of full-service and low-cost carriers are compared	Latent Dirichlet Allocation.	The most significant service quality dimensions for full-service and low-cost carriers are tangibles and reliability.
Srinivas and Ramachandiran (*14*)	Topic modeling of online reviews for US-based airlines	Latent Dirichlet Allocation.	Cabin and ground staff, in-flight entertainment, rewards program, food and beverage service, first-class and business-class service are factors for passenger satisfaction. Baggage service, seating, cabin comfort, ticket services, on-time performance are factors for dissatisfaction.
Ahmad and Rodríguez-Díaz (*34*)	Using Tripadvisor tags to predict positive or negative reviews for the airline	Sentiment analysis with machine learning.	295 tags were found to have a significant relationship with the overall rating and to assess customers' sentiments about the quality of service.
Ahmad and Rodríguez-Díaz (*35*)	Positioning of airlines on Tripadvisor according to their online popularity	Factor analysis and regression analysis were performed using Tripadvisor scores.	There was a significant difference in crucial service quality variables between airlines in different geographic areas.
Tahanisaz and Shokuhyar (*36*)	Evaluation of passenger satisfaction with the quality of service in Iran	A Kano model was applied to 372 questionnaire responses.	18 service quality attributes created from the literature were measured according to 10 different customer classes.
Liau and Tan (*37*)	Investigating consumer opinion of the low-cost airlines in Malaysia	Sentiment analysis and clustering method were conducted on Tweets.	The primary topics include customer support, ticket promotions, flight cancellations and delays, and post-booking management.

(continued)

Table 1. (continued)

Author	Objective of study	Method	Findings
Sezgen et al. (*1*)	Among full-service and low-cost carriers, attempting to study the main factors that affect the satisfaction and dissatisfaction of customers	Latent semantic analysis (LSA) used for categorization of online comments from Tripadvisor.	The staff's friendliness and helpfulness are the critical factors for economy class passengers, product value is critical for premium passengers, and a low price is the crucial satisfaction driver for low-cost passengers.
Korfiatis et al. (*38*)	Measurement of airline service quality with Tripadvisor's comments	Structural topic models (STM) used for topic modeling.	Cost and comfort are the main factors for customer satisfaction. Customer dissatisfaction is caused by delays and carriers' responses to service failures (refunds/ cancellations).
Atalik (*39*)	Analyzing customer complaints about Turkish Airlines	A survey was applied to 608 customers registered to the frequent-flyer program of Turkish Airlines.	Complaints were grouped into five categories. These groups are: lack of free tickets and upgrades of the flight class, behavior of personnel, card ownership issues, nature and level of priority services offered within the program, lack of alliance with other airlines.
Gilbert and Wong (*40*)	Identifying the service dimensions of airlines in Hong Kong	Frequency distribution and the Anova method were used with 365 questionnaire responses.	A 26-item questionnaire to assess airline service quality across six dimensions was developed.
Tsaura et al. (*41*)	Examining service quality of airlines in the United States	The fuzzy multiple criteria decision-making method was used according to 211 questionnaire responses.	15 dimensions were specified as service quality evaluation criteria.
Chang and Yeh (*42*)	Examining service quality of Taiwan's domestic airlines	The fuzzy multicriteria analysis method was used according to 354 questionnaire responses.	15 items were considered for service quality through five dimensions.

Note: AIRQUAL = airline service quality; SERVQUAL = service quality; Anova = analysis of variance.

cancellations). While there is a tendency to analyze UGC in different industries, there is no adequate level of academic research on the acquisition of knowledge from such sources in the airline industry (*31*). The sentiment analysis of online reviews is another approach using UGC that has been examined in a small number of academic research studies to detect service failure in the airline industry. A prediction method performed by a machine learning algorithm, sentiment analysis, or opinion mining decides whether user-generated text content in online discussion groups, review sites, or social media channels is positive, negative, or neutral (*50*, *51*). For example, Kwon et al. (*29*) conducted a sentiment analysis on the comments of the Skytrax website and revealed that seat, service, meal, and delay were the main issue for Asia-Pacific airlines. According to Liau and Tan (*37*), the result of sentiment analysis conducted with social media messages has shown that heavy traffic on the web page during the promotion period, flight cancellations, and delays are the main problems for low-cost airlines in Malaysia. Using the Latent Dirichlet Allocation (LDA) algorithm on customer reviews in Skytrax as a topic modeling method, Lucini et al. (*31*) recommend 27 topics to maximize airline customers' satisfaction level. According to the results, customer service for first-class passengers, comfort, and couples flying together, for premium economy passengers, and, finally, delay, price, checking luggage, and waiting times for economy class passengers are crucial for satisfaction.

As a result, sentiment analysis is used as a priority process, one of the data mining methods for detecting complaints and service failure in cases where it is uncertain whether the content has a positive or negative emotion. The problem that arises here is that while the sentiment analysis accuracy in English is high, it is difficult to achieve the same success in other languages. In their comparative study, Kaya et al. (*52*) discovered that English is more accurate in the sentiment analysis because Turkish is more morphologically rich. Though there are various polarity lexicon resources for English, the insufficient level of such resources for Turkish and many other languages is regarded as a major barrier to creating sentiment analysis tools and applications in these languages (*53*). One way to overcome this problem and reveal service failure in any industry is to use data that has negative emotions, in other words, customer complaints.

Cultural differences in customer complaint behavior and inadequacy of industry contributions in analyzing consumer comments written only in English make it inevitable that country-based studies will need to be carried out. Moreover, based on the results of the studies cited above, it is thought that the service class should be a feature to be considered in the capture of different dimensions of complaints. In this regard, this study aims to analyze complaints against two major airlines based in Turkey: Turkish Airlines and Pegasus Airlines, using the LDA algorithm to categorize them under essential topics. It aims to evaluate the complaint differences against the companies according to full and low-cost service features. The following are the research questions that were developed in the scope of the research.

RQ1: At the beginning of the COVID-19 pandemic, are there differences in consumer complaints based on low-cost and full-service features?

RQ2: Do the complaints during the COVID-19 pandemic differ from the pre-COVID-19 ones?

Latent Dirichlet Algorithm

The LDA is an unsupervised machine learning technique defined as a dimension reduction method for identifying latent topics in text document collections using a probability distribution over a vocabulary (*54*). Compared with other text mining methods such as TF-IDF (term frequency–inverse document frequency), latent semantic analysis (LSA), or probabilistic LSA, LDA is considered to be more potent in semantic annotation, generalization ability, dimensionality reduction, and mixture modeling (*55*).

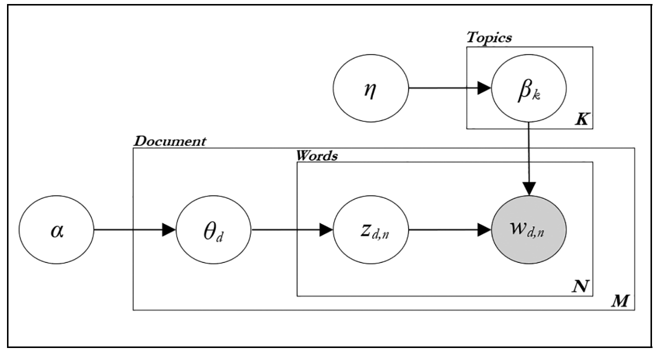

Figure 1. Graphical model for Latent Dirichlet Allocation (LDA).
Source: Adapted from Blei et al. (*54*).

As seen in the graphical representation of the LDA method in Figure 1, $w_{d,n}$ is the only observable variable expressing the words in each document. The arrows illustrate the conditional dependencies between variables ($z_{d,n}$ is the dependent variable of θ_d and $w_{d,n}$ is the dependent variable of $z_{d,n}$, β_k), while the boxes represent the plate notations used to indicate the replications (M is the number of documents, N the total number of unique words in each document, and K the number of topics). In the model, the unobservable/latent variables estimated as a result of the analysis of observable variables are as follows: β_k represents the topics and consists of the distribution of words, θ_d is the topic distribution for each document, and $z_{d,n}$ is each word assigned to the topics. η and α are the hyperparameters for the prior distribution of the per-document topic distributions (θ_d) and per-topic word distribution (β_k), respectively (*54*, *55*).

The steps of the LDA algorithm are as follows (*56*):

1. For every topic $k = \{1,\ldots..,K\}$
   a. draw a distribution over the vocabulary V, $\beta_k \sim \text{Dir}(\eta)$
2. For every document d
   a. draw a distribution over topics, $\theta_d \sim \text{Dir}(\alpha)$ (i.e., per-document topic proportion)
   b. for each word w within document d
      i. draw a topic assignment, $z_{d,n} \sim \text{Mult}(\theta_d)$, where $z_{d,n} \in \{1, \ldots, K\}$ (i.e., per-word topic assignment)
      ii. draw a word $w_{d,n} \sim \text{Mult}(\beta_{z_{d,n}})$, where $w_{d,n} \in \{1, \ldots, V\}$

The Dirichlet parameters α and η indicate the smoothing of topics in documents and words in topics, respectively. Equation 1 expresses the joint distribution of all the hidden variables:

$$p(\beta_k, \theta_D, z_D, w_D|\alpha, \eta) = \prod_{k=1}^{K} p(\beta_k|\eta) \prod_{d=1}^{D} p(\theta_d|\alpha) \prod_{n=1}^{N} p(z_{d,n}|\theta_d) p\left(w_{d,n}|z_{d,n}, \beta_{d,k}\right). \quad (1)$$

LDA, also known as a topic model method in text mining, has been employed in a variety of studies across different disciplines, such as modeling of Tweets (*57*), analyzing trends and patterns in journalist texts (*58*), topic modeling of aviation incident reports (*59*), discovering the research development and trends of scholar articles (*60*), modeling the Consumer Financial Protection Bureau (CFPB) complaints (*55*), determining the dimensions of airline customer satisfaction (*31*), and literature analysis of business intelligence in banking (*61*).

Table 2. Complaints by Month

	Pegasus Airlines	Turkish Airlines
2020		
March	492	221
April	644	264
May	267	225
June	602	1231
July	715	642
August	957	501
September	627	336
October	426	219
November	389	175
December	336	196
2021		
January	376	207
February	359	187
Grand total	6190	4404

Method

This research was based on consumer complaints collected through the website sikayetvar.com, which began operations in Turkey in 2001 and serves as a bridge between consumers and brands by publishing consumer complaints on its platform and putting pressure on brands to resolve complaints. Consumers who want to file complaints and brands who want to respond to them must register on the system. The brands' complaint resolution rates are regularly published on the platform and are accessible to all visitors. It has a total of 6.5 million users and complaints about 132,000 different brands (*62*). Table 2 shows the number of complaints about Pegasus Airlines and Turkish Airlines between March 22, 2020, and February 28, 2021. A total of 10,594 complaints from both brands were investigated in this research. It has been noted that the number of complaints, which peaked for both airlines in the summer of 2020, decreased in the first 2 months of 2021.

To prepare the complaints for LDA analysis, a five-stage process that included case transformation, tokenization, removing stop words, stemming, and n-grams was followed. Original documents were first subjected to a set of document processes, as seen in Figure 2, to classify complaints and to identify latent topics. The first step in the document process is *case transformation*.

In this step, each text is transformed to lowercase, and special Turkish letters (ö, ç, ı, ü, ğ, ç, ş) are replaced with Latin letters (o, c, i, u, g, c, s) for providing a consistent format to the documents. The next step is *tokenization*, which is the stage of separating each document into words. Special characters, punctuation marks, and numbers are removed from the text, and only words with more than two letters are considered in this step. *Removing stop words* is the third step in document processing. Words that are commonly used in Turkish (in English, words such as "I," "an," "is," or "the") are removed with a generic stop words list. Frequently repeating words, such as company names or city names, that were considered non-contributory to the analysis were also removed at this stage using a domain-specific list of stop words. There are no specific rules in creating the domain-specific word list because of the different nature of each piece of research; knowledge of the literature and the aim of the study are considered sufficient to create this list (*55*). The *stemming* method was applied in document processing to focus on the root form of the words. The stemming step is described as reducing words with the same root into a single form by removing all derivational and inflectional suffixes from each word (*63*). The stemming and stop words lists were generated within the research context without using a library set. Finally, the *n-grams* method was used in the last step to identify word pairs that are meaningful in the documents. In the n-gram step, where *n* is determined as 2, the aim was to reveal meaningful word pairs in documents such as "social distance" or "customer service."

According to the CRISP-DM (Cross-Industry Standard Process for Data Mining), developed by a consortium of DaimlerChrysler, SPSS, and NCR, the data mining process consists of six stages: business understanding, data understanding, data preparation, modeling, evaluation, and distribution. The sequence of the data mining steps is not rigid, and it is necessary to turn back and forth between them (*64*). Therefore, to determine the optimal number of meaningful topics, various words and word pairs were filtered, different parameters of LDA were used, and several analyses were conducted. Both document processing and LDA analysis were done with Rapidminer Studio 9.8 (*65*).

The most critical step in LDA analysis is the determination of the number of topics. In the literature, there are two main approaches used at this stage: qualitative

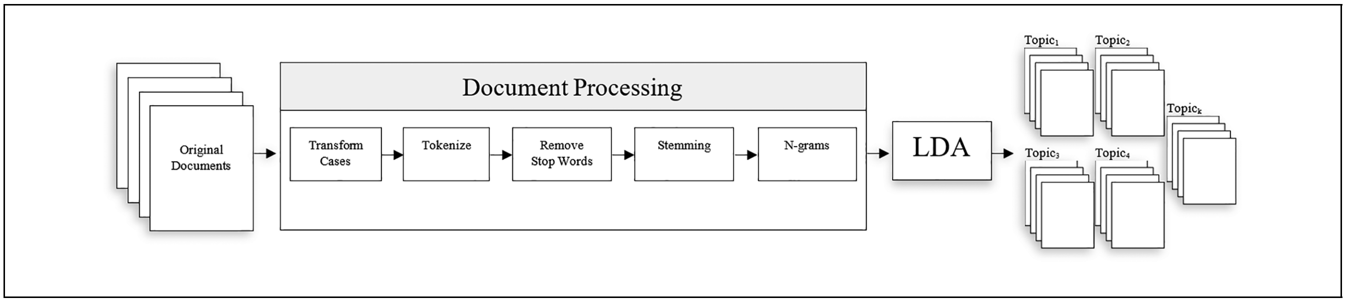

Figure 2. Text mining process.

and quantitative. As a quantitative approach, perplexity, which measures how well a probability distribution performs, is one metric that is used. According to the perplexity minimization method, lower scores indicate better predictions (*54*). However, Chang et al. (*66*) state that minimizing the perplexity score does not generate topics humans can interpret, and qualitative evaluation is required to determine the number of topics expressed as an exploratory stage rather than a predictive model. In the light of this, a qualitative approach was used to determine the number of topics in this research. The results obtained by attempting different numbers of topics were evaluated for ease of interpretation, and it was decided that it would be more appropriate for researchers into both airlines to evaluate complaints under seven topics. Tables 3 and 5 show the topics for both airlines and the weight of the top words in these topics. Labels were defined by analyzing words under each topic and their relationships via domain knowledge. Labels defined for each topic are shown in Tables 4 and 6.

Results

This section contains the results of both airlines' analyses. Topic labels, complaint distribution, and topic relations with each other are presented. Inherently, a complaint may belong to several topics as a result of the words it contains, but each complaint is only seen under the topic with the highest probability with LDA analysis. In this context, considering the probabilities of the complaints, T-SNE (*t*-distributed stochastic neighbor embedding) analysis was used to visualize the relationship of all complaints. T-SNE has been proposed by van der Maaten and Hinton (*67*) as a method to visualize high-dimensional data by assigning each data point to a two-dimensional map. These distributions are seen in Figures 4 and 6.

In this study, four topic model diagnostic measurements consisting of corpus distance, exclusivity, coherence, and tokens, suggested by McCallum (*68*), were used to evaluate the topics. *Corpus distance* measurement handles all complaints as a single topic and shows the distance of each topic from this single topic, which we can name as a general topic. Smaller values indicate a more general topic, whereas greater values mean a more specific topic. *Exclusivity* measures the degree to which a topic's top words do not appear as top words in other topics. A high value indicates that the word is more likely to appear under a particular topic. *Coherence*, a negative log probability value, is one of the topic model diagnostics metrics used to evaluate the LDA results and indicates words that tend to co-occur more often with values closer to zero. A topic with large negative values indicates that words are not often seen together. Finally, the number of words assigned to the topic is measured by tokens. Since extreme values may indicate meaningless issues, it is recommended that the researcher observe this value to reveal meaningful topics.

Pegasus Airlines

Complaints about Pegasus Airlines are evaluated in seven topics. In Table 3, the top 10 words and the weight of each word are listed. Table 4 shows the proposed labels according to the words under each topic. The number of complaints against Pegasus Airlines by topic is shown in Figure 3.

Topic 0 is thought to be primarily a category for family members' travel issues. In accordance with the regulations and guidance issued during the COVID-19 pandemic in Turkey, passengers under the age of 20 must be accompanied by their parents, and passengers over the age of 65 must present their travel permission. An important part of the complaints in this category is that the necessary information is not given during the ticket purchase process. This topic also includes the mandatory PCR tests and the issues passengers face when they are unaware of this requirement.

The most common complaints under Topic 1 are thought to be about passengers' use of the website's various features and problems when purchasing tickets. Ticket change problems, credit card issues, problems with special offer and verification codes, system timeout error, and problems with customer service, especially

Table 3. Prediction of Complaint Topics: Pegasus Airlines

Top 10 words	Topic 0	Top 10 words	Topic 1	Top 10 words	Topic 2	Top 10 words	Topic 3
Age	339	Web	1352	Suitcase	948	Open-ended tickets	832
Spouse	274	Change	407	Bag	423	Corona	641
Mother	229	Customer service	316	Check-in	323	Refund	446
Document	187	Error	253	Delivery	268	Flight cancel	434
Permission	163	Credit card	163	Be broken	161	Ticket cancel	416
Test	160	Pay	144	Cabin	155	Flight ban	310
Travel	151	Mobile	128	Damage	147	Process	294
Daughter	144	Code	121	Goods	145	Stoppage	282
Father	140	Purchase	112	Backpack	144	Pay	271
Son	125	System	102	Baggage allowance	89	Penalty	220
Top 10 words	Topic 4	Top 10 words	Topic 5	Top 10 words	Topic 6		
Passenger	482	Refund	1763	Customer service	401		
Seat	346	Flight cancel	541	Wait	191		
Corona	157	Customer service	533	CSR	124		
Social distance	108	Corona	528	Call center	113		
Empty	84	Ticket cancel	506	Code	89		
Delay	54	Request	272	Fail to reach	84		
Departure	49	My account	250	Work	77		
Mask	48	Forbidden	244	Urgent	75		
Arrival	45	Return process	228	Line	60		
Bus	43	Flight ban	176	Automatic	50		

Note: CSR = customer service representative.

Table 4. Labels for Topics: Pegasus Airlines

Topics	Label	Coherence	Exclusivity	Corpus distance	Tokens
0	Family Members	−278.75	0.74	1.77	49,647
1	Website	−328.84	0.60	1.52	61,269
2	Luggage & Cabin Baggage	−302.63	0.86	1.61	59,885
3	Open-Ended Tickets	−264.48	0.58	1.30	77,690
4	Flight and Cabin	−371.45	0.78	1.87	45,674
5	Refund	−281.96	0.49	1.20	91,042
6	Customer Service	−366.03	0.63	1.74	51,081

after such difficulties, are some of the subcategories included under this topic, and these are involved in 12.6% of all complaints.

Topic 2 presents a structure that addresses passenger complaints about baggage delivery at the counter, baggage damage, baggage allowance, and problems with hand baggage, such as not allowing backpacks as cabin baggage. Problems during check-in processes, and predominantly luggage-related problems have also appeared under this topic, such as check-in closing for baggage delivery (meaning that the passenger is late), problems in boarding the plane after baggage delivery, extra baggage charge, and negative experiences with check-in staff. In total, 13% of the total complaints fall under this topic.

Topic 3, Open-Ended Tickets, is the second most frequent complaint issue with a share of 18% during the COVID-19 pandemic. An open-ended ticket, which can be used at any time within a specific time limit and is defined as an undated travel document, appeared as the most intense core issue of Topic 3. Refunds, ticket and flight cancellations, flight bans, payment problems, penalties, authorized stoppage because of penalties, and the difficulties encountered when converting tickets purchased before the COVID-19 pandemic into open-ended tickets are subcategories that formed Topic 3. The highest coherence value of Topic 3 shows that words tend to be together more often, and relatively low corpus distance increases the probability that Topic 3 is a background topic.

It is seen that "passenger" is the word that best represents Topic 4. Seat (seat convenience, additional charge for the seat, full capacity flight, not providing side-by-

Table 5. Prediction of Complaint Topics: Turkish Airlines

Top 10 words	Topic 0	Top 10 words	Topic 1	Top 10 words	Topic 2	Top 10 words	Topic 3
Refund	882	Suitcase	864	Seat	463	Change	293
Corona	450	Bag	179	Corona	161	Open-ended Tickets	218
Ticket cancel	334	Delivery	174	Empty	106	Return ticket	213
Flight cancel	238	Broken	149	Social distance	89	Customer service	202
Customer service	188	Damage	141	Period	79	Paid	192
Check	185	Goods	125	Full	68	Corona	162
Request	180	Document	72	Check-in process	67	CSR	135
Sales office	180	Cabin	70	Middle	53	Purchasing	119
Reclaim	165	Indemnity	64	Business	52	Round trip ticket	119
Credit card	155	Baby	52	Travel	50	Web	110
Top 10 words	**Topic 4**	**Top 10 words**	**Topic 5**	**Top 10 words**	**Topic 6**		
Check-in process	424	Miles and smiles	2954	Customer service	576		
Istanbul airport	158	Feedback	347	Flight cancel	457		
Test	146	Code	342	Web	414		
Wife	136	Health	246	Change	361		
Mother	126	Discount	216	Ticket cancel	300		
Departure	100	Customer service	186	Call center	220		
Age	88	Healthcare professionals	182	Wait	214		
Permission	79	Web	180	CSR	178		
Be necessary	75	Return	126	Transfer	178		
Document	67	Call center	107	Error	134		

Note: CSR = customer service representative.

Table 6. Labels for Topics: Turkish Airlines

Topics	Label	Coherence	Exclusivity	Corpus distance	Tokens
0	Refund & Cancellation	−266.4	0.63	1.53	96,026
1	Baggage	−273.5	0.81	1.85	71,636
2	Seat & Social Distance	−336.5	0.55	1.85	71,693
3	Open-Ended Tickets	−295.9	0.44	1.58	89,438
4	Check-In & Family	−328.0	0.59	1.71	80,476
5	Frequent-Flyer Program (Miles & Smiles)	−254.3	0.67	1.73	79,500
6	Customer Service & Website	−268.5	0.54	1.55	92,266

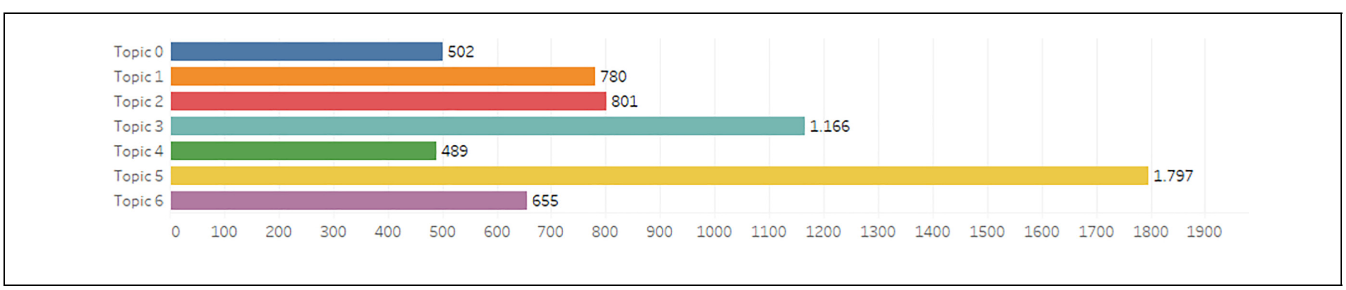

Figure 3. Number of complaints: Pegasus Airlines.

side seats for passengers traveling together are some seat related complaints), social distance, empty seats, delay (departure and arrival), and issues with wearing masks are top subtopics surrounding travel and cabin issues faced by passengers. Additionally, bus travel offers to passengers because of flight issues are included in this topic. Topic 4 has the lowest ratio of all complaints with 7.8%. The lowest coherence and tokens value and the

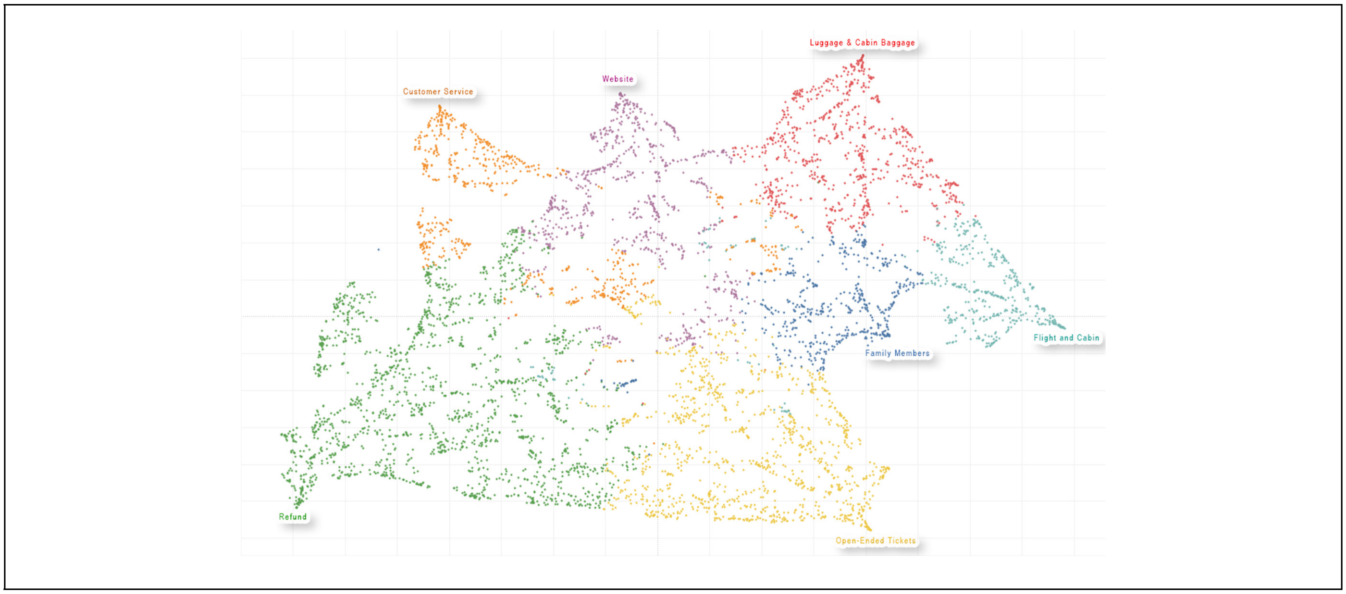

Figure 4. Distribution of complaints: Pegasus Airlines.

most significant distance to the corpus increase the probability of Topic 4 containing more unique content than others.

Topic 5, where the word "refund" has the highest representation, has a close relation to Topic 3 in its inclusion of subcategories like flight and ticket termination caused by the unexpected travel prohibition or a country ban during the COVID-19 pandemic period. Topic 5, which has the highest ratio of all complaints, with 29%, also covers issues related to customer service, requests, return processes, and the passenger's account. The relatively high number of tokens for Topic 5 together with the lowest corpus distance increase the probability of it being a background topic like Topic 3.

Finally, in Topic 6 a structure has been observed that includes consumer complaints about customer services such as failure to reach the call center, problems with the customer representative, and long waiting times on the phone line. Long wait times associated with a private call center that charges per min and difficulties in reaching a customer representative are also observed as subgroups of complaints within this topic.

Although the complaints are likely to belong to more than one topic, the LDA algorithm calculates the probability that each complaint may occur under the number of topics determined and assigns each complaint to the topic with the highest probability. Figure 4 shows the distribution of complaints performed by the T-SNE algorithm, using the probabilities of occurrence of each complaint under the topics.

The contents of some complaints within the scope of customer service appear to have relatively high probability values for the Website, Refund, and Family Members topics. It has also been revealed that some of the complaints lodged under the topics of Refund and Open-Ended Tickets have a relatively high probability value and content similarity. Furthermore, the contents of some of the complaints in Family members tend to be close to the Refund and Open-Ended Tickets topics with a high probability.

Turkish Airlines

Complaints about Turkish Airlines are evaluated in seven topics. In Table 5, the top 10 words and the weight of each word are listed. Table 6 shows the proposed labels according to the words under each topic.

According to the analysis findings of the complaints against Turkish Airlines, Topic 0 is centered on the word "refund" and shows a similar trend to Pegasus Airlines' complaint Topic 3. The subtopics in which Topic 0 differs are the sales office, traveler's check instead of refunds, and credit card issues. Topic 0 has the second-highest ratio of complaints with 19.4%. Having the lowest corpus distance value and the highest tokens increases the probability of Topic 0 being a background topic.

Topic 1, on the other hand, consists of a structure that includes "suitcase," which is the word with the highest representation and involves words directly related to the suitcase, such as "damage" and "broken," or to documents that are related with indemnity. Topic 1, which is similar to Topic 2 of the Pegasus Airlines complaints, varies in particulars with its inclusion of baby carriage, and damaged and broken baggage compensation processes. Having the highest exclusivity and corpus distance

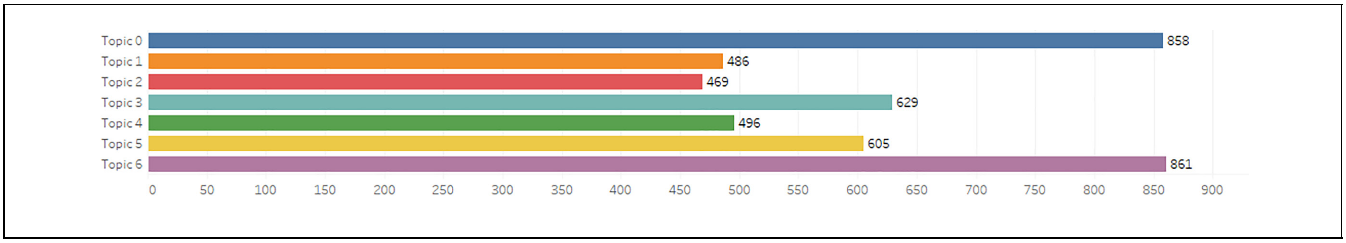

Figure 5. Number of complaints: Turkish Airlines.

value increases the possibility of Topic 1 being more special than others.

Topic 2 shows a structure mainly related to different seat assignments for family members, seat selection during check-in, not keeping the middle seat empty, additional payment for seat selection, lack of empty seats on the plane, and social distance between seats. Furthermore, problems with business-class seat reservations are included in Topic 2, which indicates a difference from the Topic 4 complaints against Pegasus Airlines. Topic 2 has the lowest complaint rate at 10.6%.

Topic 3 is best represented by the word "change," and when the complaints are reviewed, this word is strongly associated with the open-ended ticket, date, and fare. Specifically, website and customer service complaints about changes, and open-ended ticket issues, are also categorized under this topic. Open-ended tickets, which have the lowest exclusivity value, may be considered a background topic, just like the same complaints against Pegasus Airlines.

Passengers' complaints against staff at check-in, online and off-line check-in conflicts, issues with COVID-19 tests and travel documentation, and problems faced by passengers traveling with family members during check-in processes are all covered in Topic 4. Word distribution shows that these complaints mostly occur at the Istanbul Airport. Changing the gate number without warning, alleging that the passenger was late when they actually arrived on time, slow behavior of check-in staff, and missing travel documents have also been observed as complaints that result in the passenger not being able to board the plane, all within the scope of Topic 4.

Topic 5 is mainly related to Turkish Airlines' frequent-flyer program, called Miles & Smiles, and discounts. This topic also addresses issues such as problems about special discounts for healthcare professionals and having issues with promotional codes. Bad experiences of passengers with customer service during the feedback process for these complaints are also included in Topic 5.

Topic 6, which has the highest complaint rate, along with Topic 0, substantially consists of complaints arising from communication with customer service in solving problems such as flight and ticket cancellation, change, and transfer. Complaints under this topic also include long wait times to contact the call center or not being able to reach them at all. Another structure under this topic is the complaints about the website. The inability of passengers to make every transaction on the website and the errors that occur are complaints about the website, which is another structure in Topic 6. The number of complaints against Turkish Airlines by topic is shown in Figure 5.

Figure 6 shows the distribution of complaints about Turkish Airlines generated with the T-SNE algorithm. It is seen that Open-ended tickets show a distribution close to the general as a more background topic. Some complaints in the Check-In & Family topic have been found to be close to Baggage and Seat & Social Distance. Baggage appears as a more specific issue with the highest exclusivity measurement. It is seen that some of the complaints in the Seat & Social Distance topic are close to general and the Frequent-Flyer Program topic. Refund & Cancellation, on the other hand, shows a more exclusive appearance compared with its volume. Because of its nature, Customer Service is formed like a general complaint and it appears as the top word in several topics.

Cross-Validation

LDA is an unsupervised method and forces each complaint to be placed under a topic according to the word weights. Complaints can inherently fall under more than one topic, and this situation is partially seen in the T-SNE distribution, which was created considering the probability of occurrence of each complaint. Since it is not possible to evaluate and encode 10,594 complaints with an average of 75 words, the reliability of "document processing" in the model created was ensured by examining and coding 280 complaints with the highest representation capability, by two experts considering the topics according to LDA results. The probability of predicting complaints was determined by the cross-validation method using the training set. For example, the complaint below was coded as Family members:

My nephew bought a ticket from Pegasus airlines on June 24. He went to the airport on the flight date, but it was said that

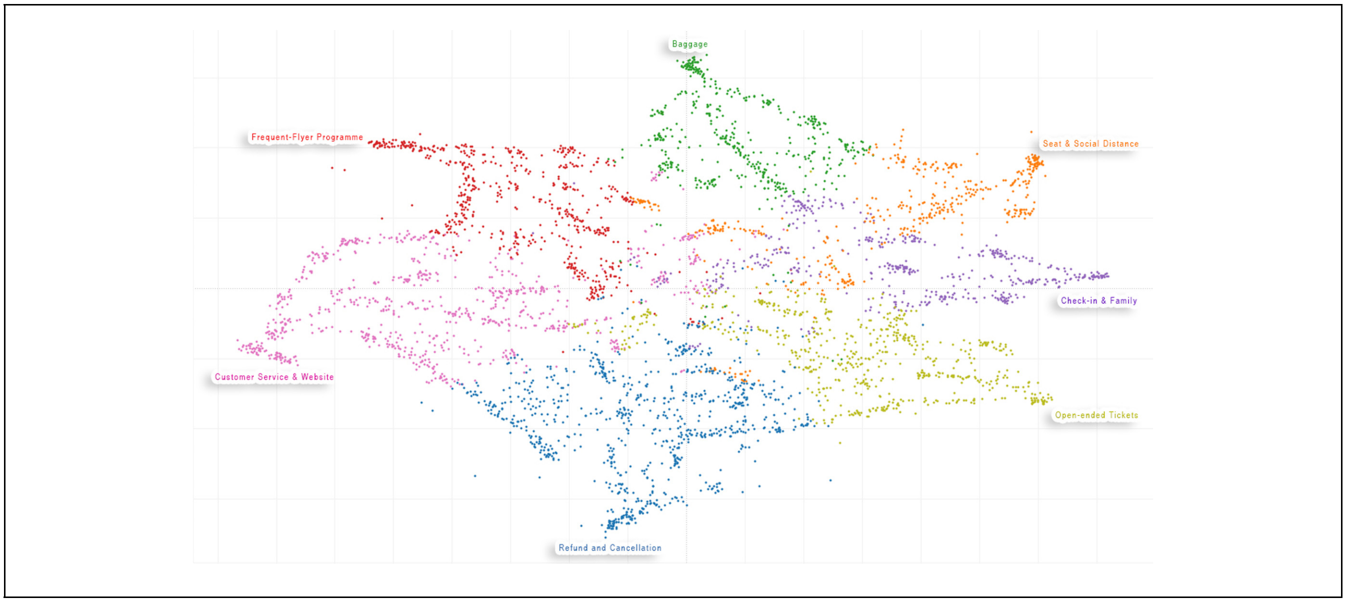

Figure 6. Distribution of complaints: Turkish Airlines.

> *he would not be taken on the plane because he was under 18. Because of this, he could not travel. Why was a ticket sold to this kid if he could not travel?*

While reviewing the following complaint, which can also be evaluated under different topics, it was coded as an Open-ended ticket in light of the LDA findings.

> *I requested a refund due to the cancellation risk for my flight to Berlin on March 20. However, on March 12, it was stated from customer service that I am not entitled to a full refund and that I only have the right to change or make an open-ended ticket. So I made it open-ended. Flights were cancelled, and I learned that those who did not make open-ended and cancelled flights were full refunded. However, it is now stated that I can only receive taxes as refunds. My visa will expire in November, and the visa processes are already closed. If I had not changed the ticket to open-ended and waited, I would have been able to get a refund (this information was never shared at the time I was changed). Many people are victimized in this way. Likewise, I have one more international ticket, which I made an open-ended ticket and suffered. I want to get a full refund for both my tickets.*

The cross-validation method divides the training set into k parts. The $k-1$ parts are put into training, and the remaining part is put to the test. The average accuracy results of all tests performed in k numbers defined as k-fold in the Rapidminer software give the confusion matrix (*69*). The confusion matrix is a table used to measure a classification model's performance on a set of test data for which the actual values are known. This table has four values: true positive, true negative, false positive, and false negative. The recall and precision values obtained from the confusion matrix result shown in Equation 2 were used for the supervised model evaluation.

Naive Bayes classifier, which is preferred in text classification and for small data sets (*70*, *71*), was used in test the model. The Naive Bayes classifier, which is used to learn the pattern by considering the word weights in the generated training data set, basically gives the $\Pr(C|d)$ output as the probability that the d document belongs to the C class (*71*).

The average score of the correct prediction in k iterations is expressed as accuracy. In this model, k is considered as 5.

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}. \quad (2)$$

The average accuracy value is 92.14%, as seen in Table 7 for Pegasus Airlines. It has been determined that the recall rates of Luggage & Cabin Baggage and Customer Service complaint topics are relatively low.

The precision and recall values of the complaints against Turkish Airlines are shown in Table 8. The Open-Ended Tickets topic was found to have a lower prediction ratio than others, and it was found that false predictions under this topic were estimated as a Refund & Cancellation topic.

The accuracy value of the model was found to be 87.86%, and the prediction powers of topics other than Open-Ended Tickets are close to each other.

Table 7. Classification Accuracy of Pegasus Airlines' Complaints

Topics (accuracy: 92.14%)	Precision	Recall
Family Members	0.86	0.95
Website	0.90	0.95
Luggage & Cabin Baggage	1	0.80
Open-Ended Tickets	0.95	0.95
Flight & Cabin	0.95	0.95
Refund	0.901	1
Customer Service	0.89	0.85

Table 8. Classification Accuracy of Turkish Airlines' Complaints

Topics (accuracy: 87.86%)	Precision	Recall
Refund & Cancellation	0.76	0.80
Baggage	0.94	0.90
Seat & Social Distance	1	0.95
Open-Ended Tickets	0.87	0.70
Check-In & Family	0.94	0.85
Frequent-Flyer Program (Miles & Smiles)	0.90	0.95
Customer Service & Website	0.76	1

Conclusion

In this research, topic modeling as a text mining method using the LDA algorithm was applied to analyze complaints against two major airlines in Turkey during the COVID-19 pandemic. Conditions for travelers in the entire transportation sector have changed because of the COVID-19 pandemic, so analyzing the complaints that have emerged in the new era is seen as an effective method, and it is thought that it is vital for companies to take quick action against service failure and thus avoid damaging their reputation. Turkish Airlines is a full-service option and Pegasus Airlines represents a low-cost service. In this context, the comparison of the analysis results and whether there is any difference between the two service options were also investigated.

Although the complaint topics modeled based on the research results are generally similar, differences in complaint content were found between the two airline companies. In this respect, the answer to the first research question asked within the scope of this research is that the complaints of both airlines differ in various ways. While complaint topics modeled under Refund, Open-Ended Tickets, Baggage, Customer Service, Family Members, Social Distance, Seat, and Website have similar complaint topics for both airlines, Frequent-Flyer Program, Business-Class Seat, Staff at Check-In, and Online/Off-Line Check-In conflicts are more prominent for Turkish Airlines. It has been observed that baggage allowance for a cabin, a private call center that charges per min, and family members' travel issues related to age are more notable complaints about Pegasus Airlines. Most of the complaints against Turkish Airlines are related to the 'refund and cancellation' and 'customer service and website' topics. Refund and Open-Ended Tickets have been found to be the most common complaint topics for Pegasus Airlines.

When the findings are evaluated for the second research question, some new factors are found at the beginning of the COVID-19 pandemic period which were not present earlier. The most apparent one is the open-ended ticket. Flight bans and customers' lack of information about the regulations are the most critical antecedents in the emergence of complaints about this issue. Also, family-related factors, especially complaints arising from travel regulations for those aged under 20 and over 65, were observed as critical complaint topics for both airlines during the early stages of the COVID-19 pandemic period. These factors were not directly encountered in the studies before COVID-19, based on Table 1. Additionally, social distance, empty seats for health safety, full capacity flights, and wearing masks are revealed as similar subtopics related to cabin issues for both carriers' customers at the beginning of pandemic, and these naturally differ from the pre-pandemic situation.

Compared with the research (*29*, *30*, *72*) conducted recently before the COVID-19 pandemic, previously common factors such as cabin staff, cabin cleanliness, meals, and entertainment were not voiced as customer complaints about either airline during the pandemic. This result indicates that during the early stages of the pandemic, passengers either ignored or did not have any negative experience associated with these issues on both airlines. However, seat and luggage factors show a similar structure in both periods in respect of consumer satisfaction for both airlines. Delay, a typical dimension in the pre-pandemic period, is more explicitly voiced to the low-cost carrier customer at the beginning of the pandemic. At the same time, check-in-related complaints are more clearly expressed for the full-service carrier.

The research findings are similar to the study results of Korfiatis et al. (*38*), which stated that refund is another critical factor of customer dissatisfaction. For both airlines, refund and related issues are complaints that have arisen during the pandemic period. Furthermore, complaints related to the website and customer services are similar to studies conducted in the pre-COVID-19 period for both airlines (*1*, *37*). In this respect, the study findings show similarity with Liu et al. (*25*), which considered the general tourist complaints in China during the early stages of the COVID-19 outbreak and found three complaint themes, which are cancellation, refund, and customer relationship management. According to a study considering North American airlines, passengers in economy class experience the refund problem more frequently in this period which is consistent with our findings (*73*).

The determination of positive and negative opinions through consumer reviews by sentiment analysis is more prominent in the literature. In this regard, we would like to emphasize that this research is focused exclusively on complaints and that we could not discover enough studies of this specific type for airline industry literature. We believe that the methodology and findings will help future studies in this field and fill this gap.

Implications for Academia and Practitioners

The results of the research are thought to have both academic and practical contributions to make. For most disciplines, survey and interview approaches are standard data collection instruments. A major challenge for these methods is determining the best sample method and reaching a large enough number of respondents. UGC is a new data source for research that has recently emerged as a result of social media applications and various web business enterprises. In situations where standard methods fail to reach the target audience and cannot collect detailed data, as in the example of complaints, which is the subject of this study, new data sources allow reaching the target audience and collecting detailed data. New data sources, which can provide highly useful knowledge, are believed to be important to use in academic research, especially in the social sciences.

It is seen that the large amount of data obtained from new sources enables the use of different algorithms used in data mining, especially in academic research on a social discipline such as marketing, branding, consumer behavior, communication, and tourism. LDA, an algorithm used for text mining that reduces large quantities of text data to a small number of topics and is expressed as topic modeling, has become increasingly popular in academic research. In this regard, this research has revealed the consistent data reduction performance of the LDA algorithm used to model airline complaints about identifying service failures.

The findings of the study support the academic literature while also revealing new dimensions for service. For example, the research findings, which are generally similar to the topics that Bellizzi et al. (*30*) defined as the leading service feature for airlines, show that Seat & Social Distance, Family Members, Refund, and Open-Ended Ticket topics appear as new specific structures during the COVID-19 pandemic. Based on these results, it is suggested that airlines should prevent such complaints by being more careful in ticketing to age groups under age 20 and over the age 65 according to the changing official rules in the COVID-19 pandemic, mainly to prevent family complaints arising from travel restrictions. This solution can also help avert ticket cancellation, refund, open-ended tickets, and customer service difficulties caused by family complaints. A feasible update and warning system for this actual problem in the ticketing system could help to reduce the number of complaints.

The study's findings are also consistent with the findings of Korfiatis et al. (*38*), which state that refund and cancellation are the most critical factors in customer dissatisfaction in the airline industry. According to this research, these are the topics that generate the most complaints against both airlines. During the COVID-19 pandemic, it was officially regulated that ticket refunds for flights canceled as a result of mutual flight bans be processed 2 months after the mutual flight bans were removed. This research cannot determine how many complaints about a refund have officially exceeded the cited period. In other words, the complaint may occur because the passengers are insufficiently informed. In this respect, telling the passenger in more detail about regulations and explaining the process should be the primary goals for airlines. Customers of both airlines frequently mention the difficulties they experienced in converting tickets purchased before flight bans and restrictions to open-ended tickets. It will be helpful to clearly state the new regulations' rules and conditions by means of simple animations and visual elements on social media and during ticketing carried out through the airline's web page. Furthermore, instead of refunding or converting to open tickets, awarding passengers with points (travel vouchers) for long-term use may be an alternative strategy of preventing complaints in situations where airline companies are under extreme economic pressure, such as the COVID-19 outbreak.

According to Sezgen et al. (*1*), flight delays, extra or hidden costs, and poor customer service are cited as the main factors of dissatisfaction for low-cost airline passengers, while baggage and flight disruptions and uncomfortable seats are noted for economy class passengers. In this study, extra or hidden costs emerged as a subtopic in the Luggage & Cabin Baggage topic and Customer Service topic because of a charge-per-min call center for the low-cost airline. Additionally, the research results support Liau and Tan (*37*), who defined the web page issues, flight cancellations, and delays as the low-cost carrier's main problems in Malaysia. Low-cost carriers should regulate or not charge telephone call rates, especially in extraordinary situations. Developing a system for resolving complaints through the official website and encouraging customers to use it will be an essential alternative strategy for both airlines. This data will undoubtedly offer new opportunities for customer relationship management and will help carriers become more customer-centric.

Atalik (*39*) defines passenger complaints under five topics in research conducted on Turkish Airlines frequent-flyer program passengers. Although the research findings include a similar pattern, especially for personnel-related complaints, the issues that emerged as a result of promotional events for healthcare professionals at the beginning of COVID-19 come to the forefront under this heading for Turkish Airlines. These complaints are mainly triggered by technical issues such as not receiving a password or promotional code. In such extraordinary situations, it is thought that these complaints will decrease significantly by giving more weight to customer service, increasing the number of personnel, and solving technical problems.

Limitations and Future Research

The main problem for UGC data obtained from social media or different web applications is the lack of demographic information. Therefore, it is an important limitation that the analysis results cannot be compared against demographic variables such as gender, age, education, or income. The complaints in this study were unstructured data obtained from an online source. Another limit in this research is the inability to clear data, such as when a disappointed customer repeats a complaint with different usernames, reflects the problem differently, or makes the issue appear larger than it is.

The LDA method used in the analysis for modeling complaints is based on probability and does not reflect the actual count. Therefore, it is difficult to assess whether all complaints have been properly classified. Although the LDA method gives valuable information in exploratory research, future studies can reach better results using supervised machine learning methods. Additionally, the complaint may belong to more than one topic because of its nature. In this context, each complaint's topic has been shown graphically with the T-SNE analysis based on probability value. It is thought that it is crucial to reveal subtopics by considering these topics in new studies.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: L. Çallı, F. Çallı; data collection: L. Çallı, F. Çallı; analysis and interpretation of results: L. Çallı, F. Çallı; draft manuscript preparation: L. Çallı, F. Çallı All authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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