Journal of Air Transport Management, Volume 77, June 2019, pp. 65-74
DOI: 10.1016/j.jairtraman.2019.04.001

Article Title: Voice of Airline Passenger: A Text Mining Approach to Understand Customer Satisfaction.

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Highlights

- Fundamental differences in the drivers of passenger satisfaction based on cabin class and business model.
- Friendliness of staff is the common factor driving satisfaction for all passenger groups.
- Deficiency of hygiene factors causes an excessive level of dissatisfaction.

Voice of Airline Passenger: A Text Mining Approach to Understand Customer Satisfaction.

Abstract

This paper investigates the key drivers of customer satisfaction and dissatisfaction towards both, full-service and low-cost carriers and also towards, economy and premium cabins. Latent Semantic Analysis - a text mining and categorisation technique – is applied to analyse online user-generated airline reviews. Over five thousand passenger reviews for fifty (50) airlines were collected from the online review site, TripAdvisor. Findings show that there are fundamental differences in the drivers of passenger satisfaction depending on the class of air travel purchased, and whether the airline is a low cost or a full service carrier. Friendliness and helpfulness of staff are the key factors for those travelling in Economy Class, product value is key for those in premium cabins, and a low price is the key satisfaction driver for those that choose to travel on a low cost airline. The research also shows that the service attributes seat comfort and legroom, luggage/flight disruptions and staff behaviours are the main reasons for passengers' dissatisfaction among all groups. This study provides an alternative customer satisfaction analysis for managers to hear the voice of their customers by using a well-established text mining technique and by analysing the reviews of satisfied and dissatisfied customers.

Key Words: Customer satisfaction, text mining, airlines, Latent semantic analysis, marketing

1. Introduction

Fierce competition in the airline industry requires effective customer relations management both online and offline to retain customer satisfaction, and so drive future income. Customer feedback, in particular, is critical since it is an actuator source for business growth and performance, improvement of customer experience and innovative product and service offerings (Siering et al., 2018). Satisfying passengers and translating this satisfaction into behavioural commitment is key for airlines to remain competitive.

There are numerous ways to asses and address customer satisfaction, and behavioural intentions. Managers generally rely on customer feedback both to identify future managerial goals and to monitor the performance of a firm through customer satisfaction and loyalty scores, such as Net Promoter Scores and average customer satisfaction scores (Morgan and Rego, 2006). The International Air Transport Association (IATA) provides a passenger satisfaction benchmarking study called Airs@t. The scale incorporates 70 travel attributes including pre-flight, in-flight and post-flight attributes of overall travel experience (IATA, 2018). In the academic context, various service quality frameworks—SERVQUAL, AIRQUAL, Kano and SERVPERF— have been used to investigate the relationship among airline service quality attributes, and satisfaction, and loyalty (Chiou & Chen, 2010; Chen, 2008; Park et al., 2004; Ekiz et al., 2006; Basfirinci and Mitra, 2015; Hussain et al., 2015; Rajaguru, 2016). Antecedents and drivers of airline passenger satisfaction and loyalty (Forgas, Moliner, Sánchez, & Palau, 2010; Mikulić & Prebežac, 2011; Akamavi, Mohamed, Pellmann, & Xu, 2014; Vlachos & Lin, 2014) and/or airline service attributes (Vlachos & Lin, 2014; Medina-Muñoz, Medina-Muñoz, & Suárez-Cabrera, 2018) have also been investigated by a number of researchers. A large number of airline service attributes identified and used in the literature (See Appendix A) to analyse how these attributes lead to customer satisfaction, loyalty and willingness to recommend are either based on airline business model and/or service class, or are at an aggregated level. However, there is no agreement reached in the literature on which service attributes establishes service quality and satisfaction (Medina-Muñoz et al., 2018). It is critical to understand what the key service attributes leading to passenger satisfaction are and how they differ among different airline business models and service classes.

Online platforms (such as Twitter, Facebook and Skytrax) allow customers to share information, opinions, and knowledge about products, services and brands (Filieri and

McLeay, 2014). Today, an increasing number of consumers read and share online travel-related content particularly if those are posted or created by their friends (Gretzel et al., 2007). Customer feedback and reviews on online fora are boosting the expansion of word-of-mouth (WOM) on the web (Filieri and McLeay, 2014). They are especially relevant for service industries because of intangible characteristics of services which include purchase risks (Nikookar et al., 2015). Sotiriadis and van Zyl (2013) found that online reviews and recommendations affect the decision-making process of tourists towards tourism services and WOM has a significant impact on the subjective norms and attitudes towards an airline, and a customer's willingness to recommend (Nikookar et al., 2015). According to the Pew Research Centre (2016), 82% of US adults tend to read online reviews and ratings prior to purchasing a product or service for the first time. In the US, reading reviews is particularly common for those who under 50. In the age group 18-29, 53% and in the age group 30-49 year 47% always read reviews when buying something first time. This proportion is lower in the 50-64 age group at 34% and 23% for 65 and older. Although reading reviews is popular, one-in-ten of Americans *always* share, and almost 50% *sometimes* share reviews about product and services they used (Smith and Anderson, 2016).

The increasing presence of customer engagement in online fora provides a large amount of useful data for airline marketers and researchers. Effective analysis of these unstructured data can enable real-time customer feedback analysis, compared to traditional data analysing techniques (Liau and Tan, 2014). Although it is desirable for airlines to assess customer satisfaction, and to put forward remedial actions, it appears difficult to obtain genuine passenger feedback through traditional methods. The majority of customers are not always willing to share genuine feedback with their service provider, particularly feedback about their dissatisfaction (Berezina et al., 2016). Research shows that complaint behaviour of airline passengers varies based on demographic characteristics, and they voice their complaints either directly to the company or privately (WOM) or via a third party platform (Kim and Lee, 2009). It would be very useful for airlines to better understand their diverse customer base in order to take service improvement strategies since airlines are inherently multicultural businesses. The internet enables airlines to do this as customers share their experiences through various online platforms (Berezina et al., 2016). However, only a few studies in the airline sector have used online customer-generated content by conducting sentiment analysis of fora such as Twitter (Liau and Tan, 2014; Misopoulos et al., 2014) and Skytrax airline reviews (Siering et al., 2018; Xu et al., 2018) to identify critical elements of airline services.

Online data are generally unstructured, and it is very difficult to analyse this large amount of data manually and objectively. However, this study uses a well-established statistical method, Latent Semantic Analysis (LSA) that reveals hidden meanings in unstructured data. The main purpose of this study is, therefore, to analyse airline user-generated reviews to identify which service attributes lead to passenger satisfaction and dissatisfaction based on different airline business models and service class.

The main contribution of this study is to investigate TripAdvisor customer reviews of airlines through the use of a well-established text mining method (LSA). To the best of the authors' knowledge, no previous research has been undertaken using LSA technique, and TripAdvisor reviews in an airlines context. Furthermore, contrary to previous research, this study does not only consider passenger satisfaction attributes, but also takes into account customer dissatisfaction attributes and their importance rankings, by comparing airline business model and service class. This study also offers an alternative method to airlines to assess the satisfaction and dissatisfaction of their customers.

The paper is structured as follows; Section 2-3 explains theoretical background and relevant literature. Section 4 gives background information about LSA, Section 5 explains the research method including data collection, and LSA application, Sections 6 and 7 present research findings and discussion, and finally Section 8, concludes with a discussion and implications of the findings, and considers future research requirements.

2. Theoretical Background

2.1. Customer Satisfaction

Customer satisfaction is an output resulting from purchase or consumption and it emerges from the customers' comparison between the benefits and costs together with the expected consequences. It can be assessed as the cumulation of the satisfactions originating from various product and/or service attributes (Churchill and Surprenant, 1982). Oliver's (1980) approach to customer satisfaction has widely accepted in the literature who expresses customer satisfaction as a function of expectation and expectancy disconfirmation.

This research is also grounded on expectancy disconfirmation theory which explains customer satisfaction and dissatisfaction. The theory suggests that consumers have expectations about a product or service prior to its purchase which then becomes a standard for them for the product or service in question. Once the product or service is used, the outcomes or perceptions are compared to pre-purchase expectations. This comparison leads to three scenarios, if the perceived performance matches with expectations, confirmation (satisfaction) occurs, if the expectations are exceeded, positive disconfirmation occurs, and if the expectations are not met negative disconfirmation (dissatisfaction) occurs (Yuksel, 2001).

Distinguishing airlines from one another in terms of their business models, and describing them by using a uniform formulation is difficult, especially considering the dynamic nature of the industry (Mason and Morrison, 2009). However, from the customer point of view, expectations prior to purchase, and perceptions after consumption of airline service may differ based on the airline's business model due to the nature of service and products offered by low-cost carriers (LCCs) and full-service network carriers (FSNCs) may show differences. Passengers may form different expectations for low-cost carriers and as opposed to full-service carriers, which then translates into dis/satisfaction based on their overall assessment of service performance and expectations from the airline.

Similarly, different products of an airline (economy/premium) may also form different passenger expectations and perceptions which lead to dis/satisfaction based on service delivered. Consumer utility expectations may increase proportionality to the amount they pay. Since value is a trade-off between what you give and what you get, value perceptions form customer expectations and perceptions, and so their satisfaction towards the different service classes (Zeithaml, 1988). Economy and premium passengers may value different service attributes differently and therefore their satisfaction level would differ since passengers' level of service expectation regarding service class would determine their level of satisfaction (Laming and Mason, 2014).

3. Literature Review

3.1. Customer satisfaction and airline business model and service class.

Continuous customer interest in products or services can be provided by ensuring a satisfactory purchase experience which can lead to repeated purchase behaviour (Oliver, 1993). There is a large number of service marketing literature that identifies the critical impact of service quality and customer satisfaction on purchase intention formation (Taylor and Baker, 1994). The importance of customer satisfaction has attracted great deal of interest on this topic for researchers who are interested in understanding customer purchasing behaviour. Various studies in this area confirm that there is a positive relationship between airline customer satisfaction and brand loyalty and/or behavioural intention (Park et al., 2004; Forgas et al., 2010; Hussain et al., 2015; Rajaguru, 2016). Additionally, a number of literature below highlight that there are different drivers of satisfaction for both full-service and low-cost passenger and economy and premium passenger.

Forgas, Moliner, Sánchez, & Palau, (2010) conducted a survey on passengers of three airlines, operating the Barcelona-London pair, to find out the antecedents of passenger loyalty based on low-cost carrier (LCC) versus full-service network carrier (FSNC) business models. They found that satisfaction and trust are the main antecedents of passenger loyalty for both types, whereas there are significant differences in the antecedents of satisfaction based on business types. While service quality and monetary cost are the main attributes that make satisfaction for LCC passenger, professionalism of the staff is the key satisfaction attribute for FSNCs. Similarly, the effect of value for money and service quality on customer satisfaction and behavioural intention on both airline types is examined by Rajaguru, (2016) through a survey on 15 FSNCs and 6 LCCs customers. It is found that value for money is the main determinant to achieve satisfaction and behavioural intention for LCCs, whilst the balance between value for money and service quality attributes is important for FSNC passengers. Similarly, Kos Koklic, Kukar-Kinney, & Vegelj, (2017) found a strong positive relationship between customer satisfaction and quality of staff and airline tangibles (seat comfort, leg room and extra offers) for FSCs than LCCs. Lee et al.'s (2018) results also support previous research that they found significant differences in service expectations, satisfaction and loyalty formation of LCCs and FSC passenger. On the other hand, Loureiro & Fialho, (2017) in their study, based on 304 airline passengers' flight experience in Europe, in which they examined how in-flight ambiance (temperature, odour etc.), space/function (seat configuration/comfort, in-flight amenities etc.) and crew attributes lead to satisfaction, trust, affective commitment, and finally behavioural intention. They did not find significant differences in the antecedents of satisfaction for FSNCs and LCCs.

Previous research shows that passenger perceptions differ based on service class. Park (2007) conducted a survey to analyse the purchase behaviour of airline passengers in different segments with 11 factors for both Korean and Australian passengers. He found that business/ first class passengers rate value of service, in-flight service and overall service quality higher than economy passengers. Similarly, An & Noh (2009) in their study found that six attributes are important for premium passengers respectively; alcoholic beverage and non-alcoholic beverage, responsiveness and empathy, reliability, assurance, presentation style of food, and food quality, whereas five attributes are observed as important for economy passenger in descending order; responsiveness and empathy, food quality, alcoholic beverage, non-alcoholic beverage, and reliability. Vlachos & Lin (2014) in their research specified 10 key attributes based on a review of literature and interviews. Their survey of 462 business passengers found the relationship between attributes and loyalty of business passengers. Reputation, in-flight service, frequent flyer program, and aircraft were found to be the main attributes driving business passengers loyalty. Similarly, Dolnicar, Grabler, Grün, & Kulnig (2011) found that loyalty programs are key to business passengers' loyalty.

Most of the previous research on airline passenger behaviour confirms the difference of the drivers of passenger satisfaction and loyalty for different airline business models and cabin class and they emphasis on the difference of passenger expectations. However, there is no consensus reached in the literature which service attributes or set of attributes establishing passenger satisfaction for different business models and cabin class. Therefore research used or identified the service attributes for a particular region or markets or they are validated for a particular markets (e.g. Lee et al., 2018; Forgas et al., 2010). It could be quite important to determine these key attributes in a broader context. As well as, examination of user generated reviews would be complimentary to the traditional research and it may enable a comprehensive examination of customer satisfaction due to the open structure of the reviews and the availability of reaching a large number of passengers and the anonymity of respondents (Xu et al., 2017).

3.2. Customer Dissatisfaction

Passenger interaction with an airline does not necessarily result in satisfaction. Dissatisfaction is an apparent reality in the industry usually. When the expectations are not met, negative disconfirmation occurs due to the gap between passenger expectation and service performance perceptions. Failure in the service delivery often results in customer dissatisfaction and complaint behaviour such as; negative word-of-mouth (WOM), complaints, and customer turnover (Lee et al., 2011). It is, thus, very important to understand the attributes that lead to passenger dissatisfaction. Kano, Seraku, Takahashi, & Tsuji, (1984) explain these attributes in their customer satisfaction model, under two categories; "must-be" and "one-dimensional requirement". Particularly unfulfilled "must-be" elements cause excessive dissatisfaction, but their presence does not enhance satisfaction since they are perceived as guaranteed features. On the other hand, customer satisfaction increases proportionally when "one dimensional" requirements are realised (Matzler and Hinterhuber, 1998).

4. Latent Semantic Analysis (LSA) Background

LSA is realised throughout the computation of high-dimensional semantic vectors, or context vectors of words from their co-occurrence statistics (Kanerva et al., 2000). Fundamentally LSA uncovers common factors by collecting all of the context within which words appear (Sidorova et al., 2008). LSA uses a system of coordinates of reduced dimensionality to link similar ideas, and its foundation emerges from a vector space model (VSM). In the VSM, documents (passenger reviews) are considered as a bag-of-words and the grammatical and syntactical structure of a text are disregarded. Documents are transformed into a mathematical vector in a multi-dimensional space and every single term (word) in the document library refers to a dimension (Visinescu and Evangelopoulos, 2014).

The usage of automatic text mining and natural language processing (NPL) methods has gained increasing attention in academic research to analyse unstructured texts. However LSA provides a range of advantages over other frequency-count methods (Ahmad and Laroche, 2017). LSA is completely automatic mathematical and statistical method and it does not use human-built dictionaries, knowledge bases, semantic networks, grammars, syntactic, parsers, and morphologies as in traditional NLP or artificial intelligence software (Landauer et al., 1998). It is suggested in psychology research that LSA works in a similar way as the human brain interprets text meaning (Sidorova et al., 2008).

In this study, the well-accepted statistical text analysis technique, LSA will be used because of its advantages over other techniques. The manual analysis of unstructured textual data, a sample of 5,120 reviews, is not practical enough using traditional qualitative methods, so text mining methods come into play to render them in an interpretable form (Lee et al., 2010).

5. Methodology

5.1 Data Collection

The data for this research are gathered from TripAdvisor.com, a website which enables travellers to review and share their experiences, photos, express their views on hotels, airlines, restaurants, and destinations (Berezina et al., 2016). TripAdvisor examine all the data entered by the users to make sure they comply with content guidelines. Approved reviews are posted on the hotel/airlines page. Summary rating scores are provided as a result of user ratings (O'Connor, 2010). After the introduction of an airline reviews platform in 2016, users can access user-generated information about airlines or they can review their flight experiences. Additionally, the website allows users to rate both their overall flight experience and specific experiences about seat comfort and customer service to demonstrates their satisfaction level with an airline on a five-point scale.

For this study, 5,120 user-generated airline reviews, 2,584 positive and 2,536 negative, were collected from the website. The sample only include reviews written in English by international passengers (and excludes passengers travelling domestically). The sample covers reviews of the top 50 most valuable airline brands from around the world. The airlines were selected proportionally to their global market share based on Revenue Passenger Kilometres (IATA, 2018b), the global market share of airline business models (Full-service/ legacy 77% and leisure/ low-cost 23%) (IATA, 2017) and passenger class (economy 82%, premium-class 18%). Brand Finance's annual report of airline brand values (BrandFinance, 2018) was used to select the most valuable airline brands in the world. However, only 45 airlines on the list are considered for the sample since the remaining five (Hainan Airlines, Shenzhen Airlines, Juneyao Airlines, Xiamen Airlines, and Shanghai Airlines) did not have a sufficient number of reviews for the data collection period (See 45 airlines from; BrandFinance, 2018). Instead, the following airlines were selected to be included in the sample by assessing the market shares in their respective regions (LATAM, Aeromexico, Avianca, Hawaiian, and Ethiopian). Based on these two criteria, the airline sample is distributed by region as follows; 2% Africa, 34% Asia-Pacific, 28% Europe, 6% Latin America, 10% Middle East and 20% North America, and by airline type; 22% low-cost, 78% traditional.

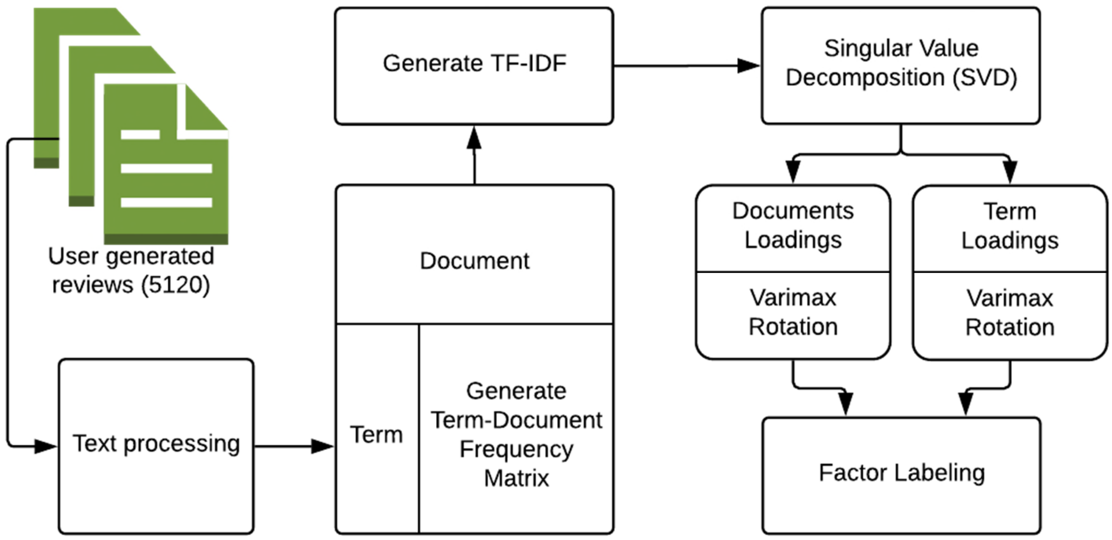
On average 102 airline passenger reviews (includes positive and negative) per airline –reviewed in the 12 months period between January 2017 to December 2017– were collected based on predefined indices for each month (beginning, mid and end of month) with the purpose of elimination of any seasonality impact on reviews. In certain periods of the year, customer complaints or satisfactions may gather due to seasonality (peak) or industry-specific factors like weather, strikes. For each review, user-related information (country, contribution level (calculated based on the number of previous reviews) and the number of reviews), date of review, overall satisfaction rating, review, and cabin class information were collected.

5.2 Data Analysis

5.2.1. Steps and Application of LSA

In line with previous studies (Sidorova et al., 2008; Yalcinkaya & Singh, 2015; Kulkarni, Apte, & Evangelopoulos, 2014; Xu and Li, 2016; Ahmad and Laroche, 2017) Latent Semantic Analysis is realised in the following four steps; 1) textual data processing, 2) term frequency-inverse document frequency transformation and singular value decomposition, 3) analysis of factors, and 4) factor rotation and labelling (Figure 1).

Figure i
Latent Semantic Analysis process



Source: Generated based on previous LSA applications (Sidorova et al., 2008; Yalcinkaya & Singh, 2015; Kulkarni et al., 2014; Xu and Li, 2016; Ahmad and Laroche, 2017).

Step 1: *Quantification of textual data (Text processing)*

Airline passenger reviews are separated into positive and negative reviews for each airline business model and passenger class. The dissatisfied economy passenger analysis will be used as an example to clarify the LSA process. The following procedures are applied to process the data sets in Rapid Miner 9.0 studio and Matlab for the subsequent analysis; customer reviews are transformed into lowercase letters. The reviews are then broken into small units by a tokenisation function with a non-letter separator, and tokens with fewer than two letters are removed since these words do not present meaningful information. After tokenisation, English stop words like "the", "and", "so" and "is" are filtered/removed, and airline names removed from the analysis. Then term-stemming techniques are applied in which different variants of the word such as; "absolutely", "absolute", "absoluteness" are truncated into the single token "absolut" in order to bring single word concepts together. As the last step, an N-grams algorithm is applied to identify phrases in which two terms are often found together throughout the data such as; "leg_room", "comfortable_seat". Consequently, initial term-by-document matrices are generated for positive and negative reviews for each airline business model and service class.

An initial term-by-document matrix (of 68,186 x 1,545) was generated as a result of this term processing. 81% of terms are removed from the matrix since 55,158 of the terms (tokens) occurred once only in one document and resulting 13,020 x 1,545 term-by-document. However, the matrix was still large enough for effective subsequent analysis. A prune method is applied (Yalcinkaya and Singh, 2015) by which any terms occurring less than five times in the dataset are removed which results in a final 3,309 x 1,545 term-by-document matrix for further analysis.

Step 2: *Term frequency and inverse document frequency (TF-IDF) weighting of the term-document matrix and dimensionality reduction with SVD*

The 3,309 x 1,545 term-by-document matrix was then subjected to a preliminary TF-IDF method, where the relative frequency of a word in a particular document identified against the inverse proportion of that specific word over the whole document corpus. In other words, this calculation demonstrates the relevancy of a given word in a specific document (Ramos, 2003). TF-IDF is calculated as follow;

$$idf_i = log_2\left(\frac{N}{n_i}\right) + 1$$

TF-IDF (weighted) score is calculated by; $w_{ij} = tf_{ij} * idf_i$

idf_i = demonstrates the rarity of term i in the entire corpus, N = the number of documents in the corpus, , n_i = the term frequency of term i in the entire corpus, and tf_{ij} = the number of occurrences of term i in document j

Using this method, rare terms are promoted whereas, more common words are given less weight (Sidorova et al., 2008; Husbands et al., 2005). As a final step, the TF-IDF weighted 3,309 x 1,545 term-by-document matrix is subjected to singular value decomposition (SVD) analysis. SVD is a variation of a factor analysis (Landauer et al., 1998). SVD is defined as *"X = WSP"*. *X* refers to a weighted matrix of terms-by-documents (words-by-reviews). SVD analysis decomposes the weighted terms-by-documents matrix into three matrices. The two orthonormal singular vectors, *"W"* and *"P"* correspond to terms and documents respectively, and the last one to a diagonal *"S"* matrix of singular values (square roots of eigenvalues) (Landauer et al., 2004). The singular values demonstrate the importance of each factor in descending order. Multiplication of singular values with singular term vectors generates a term-by-factor matrix of term loadings and, in the same way a document-by-factor matrix of document loadings is produced (Sidorova et al., 2008). The number of factors produced in this way is equal to the number of documents (1,545 in this study). To assess the key service attributes, the number of factors are reduced via dimensionality reduction (Yalcinkaya and Singh, 2015). The optimum number of factors is retained for each data set based on following procedure.

Step 3: *Identifying the number of factors reflecting key service attributes leading customer satisfaction and dissatisfaction.*

As is in factor analysis, LSA enables researchers to identify or specify the number of relevant factors in a dataset and to determine the level of aggregation so that common themes are identified (Sidorova et al., 2008). However, identifying the optimum number of dimensions is one of the open research areas that proceed from dimensionality reduction in the principal component analysis. The issue is addressed by authors differently such as; empirically testing and comparing different level factor solutions, quantitative estimation approach, and a more common approach is to use a scree plot of eigenvalues. Once the plot is drawn, diminishing returns or the “elbow” point is considered to decide the number of factors (Evangelopoulos et al., 2015). To identify the numbers of factors in this dataset, both a scree plot is drawn, and empirically different levels of factors are tested for each corpus and then the optimum meaningful number of factors is decided via examination of associated words.

Step 4: *Factor Rotation and Labelling*

Factor rotation in traditional factor analysis makes interpretation of factors easier by simplifying factor associations (Sidorova et al., 2008; Yalcinkaya & Singh, 2015). Once the number of factors is decided, Varimax rotation is applied with the purpose of increasing the variance of the factor loadings, which either maximise factor loadings or minimise them under a specific factor (Visinescu and Evangelopoulos, 2014) thus the associations between factors and loading variables become clear which makes factor interpretation more easy (Evangelopoulos et al., 2012). Varimax rotation is applied both on to the term and document loadings so that they can be interpreted in the same semantic space. Both terms and documents are reviewed together for each factor solutions so that they can be labelled. As the last step, extracted factors for both terms and documents are reviewed and interpreted by two researchers independently through the examination of high-loading terms and documents. Discrepancies are eliminated with a final discussion.

6. Results

A Latent Semantic Analysis, as described above, was applied to airline passenger reviews in order to assess service attributes that lead to customer satisfaction and dissatisfaction for LCC, FSNC and premium passenger. The results of LSA are shown in the Tables 1 and 2. These tables include satisfaction (Table 1) and dissatisfaction (Table 2) attributes, the high-loading terms associated with each factor, and a ranking (singular values) of satisfaction and dissatisfaction attributes based on airline business model and service class. The singular values (Eigenvalues) demonstrate the importance of each factor in descending order (Sidorova et al., 2008). The higher a singular value is, the greater that factor’s importance.

6.1. Positive Reviews

As a result of the examination of satisfied customer reviews with LSA, three factors were retained for economy class passengers. Four factors were retained for customers of premium cabins and three factors for passengers using LCCs (Table 1). For each passenger group, factors are labelled both by examining the associated terms and the passenger reviews falling under a particular factor. Then the extent of each factor labels are explained in the section below.

Table 1
Factors related to customer satisfaction and associated terms.

Factors	Singular values	High loading terms
Economy cabin passengers		
F1	4.073	Great, great_service, staff, great_staff, service, great_experience, experience, friendly, great_flight, staff_friendly, professional, friendly_staff, excel, travel, helpful, polite
F2	2.020	Crew, check, airport, connect, time, arrive, good_food, connect_flight luggage, cabin, flight, board, hour, air, book, cabin_crew, plane, get, journey, destination, customer_service, efficient
F3	1.887	Good, comfortable, seat, nice, great, good_service, seat_comfort, entertainment comfortable_seat, leg, excel, room, leg_room, comfortable_flight, space
Premium cabin passengers		
F4	2.372	Money, worth, recommend, value, upgrade, nice_food, class, crew, trip, flight, value_money, airline, outstanding, entertainment, extra, staff, upgrade_class, priority
F5	1.335	Respectful, aspect, exceptional, nice, helpful, happy, airline, friendly, staff, flight_staff, friendly_helpful, efficient, friendly_staff, flight, quality
F6	1.213	Menu, nice, style, western, standard, feel, nice_food, meal, choice, food, love, dish, super, vegetarian, plenty, food
F7	1.199	Good, excel, great, wine, food, service, good_service, entertainment, seat, bed, on-board, comfort, food_wine, plane, great_service, flat, service_good, smile
Low cost airline passengers		
F8	2.851	Cost, time, price, low, low_cost, airlin, company, cheap, budget, board, plane, check, air, service, travel, budget_airline, paid, money, good_price
F9	1.715	Love, friendly_staff, frill, accommodate, easy, friendly, staff, efficient, polite, found, hostess, get_good, smile.
F10	1.613	Attendant, excel, enjoy, great, crew, made, trip, kind, flight_attendant, nice, person, flown, love, rate, funny, flight, service, flight_crew, excel_ service

Economy cabin passengers

- *Factor 1 (Friendly-helpful staff):* In this factor, passengers express the friendliness and helpfulness of staff and this is linked with the greatness of service. The main expressions clarify the factor are; *"*great_service", "friendly_staff", "helpful".
- *Factor 2 (Hassle-free customer experience and care):* This factor is about the overall assessment of passenger journey ranging from check-in, airport, connecting flights, baggage claim and boarding.
- *Factor 3 (Comfortable seats and legroom):* Passengers put particular attention to the comfort of seats and the sufficiency of leg room.

Premium cabin passengers

- *Factor 4 (Value):* This factor corresponds to cost-benefit ratio. In this factor, the passenger compares the amount of extra money paid for the premium product with the overall worth of experience or service.
- *Factor 5 (Friendly-helpful staff):* Similar to economy passengers, staff attitudes are quite important for premium passenger to establish satisfaction with an airline.
- *Factor 6 (Food and beverages):* In this factor passengers emphasise the availability of different food options. "Menu", "choice", and "plenty" are the main words associated with the factor.
- *Factor 7 (In-flight service):* This factor corresponds to the overall inflight service assessment of passenger ranging from core aspects; seats, IFE and food, to customer care and attentiveness of staff.

Low-cost airline passengers

- *Factor 8 (Low price):* Low fares are the main factor that drives passenger satisfaction for LCC passenger. The value in this factor is price. It does not directly reflect the trade-off between quality and price. "Cheap", "price", "good_price" are the main words associated with this factor.
- *Factor 9 (Friendly and courtesy of staff):* Friendliness of staff is an important attribute for LCC passengers. The "staff" in this factor correspond to all staff from check-in to arrival.
- *Factor 10 (Good cabin crew service):* This factor particularly corresponds to cabin crew and it evaluates the overall cabin crew service.

6.2. Negative Reviews

Dissatisfied customer reviews are examined with LSA which resulted 4-, 3- and 5-factors solutions for economy, premium and LCC passenger respectively (Table 2). Similar to positive reviews, factors are labelled based on the associated words and the customer reviews for the specific factors.

Table 2
Factors related to customer dissatisfaction and associated terms.

Factor	Singular values	High loading terms
Economy cabin passengers		
F1	3.382	Seat, leg, entertainment, economy, uncomfortable, poor, room, leg_room, comfort, old, plane, class, space, legroom, cabin, aircraft, cramp

F2	1.914	Luggage, delay, day, customer, bag, connect, call, told, hour, cancel, book, airport, air, help, check-in, customer_service, lost, wait, miss
F3	1.796	Crew, staff, knowledge, require, crew, staff, cabin_crew, flight_crew, crew_member, apology, airways, language_barrier, major, inconvenient, ground_crew, air_hostess
F4	1.661	Bad flight, bad_food, bad_service, food, service, bad_bad, average, avoid_future, dirty, future, avoid, attendant, beer, control, flight_attendant
Premium cabin passengers		
F5	2.169	Respect, passenger, cancel_flight, communication, paid, curtain, separate, steward, paid_business, economy_passenger, hassle, treat, unacceptable
F6	2.044	Old, seat, plane, expect, interior, business_class, comfort, clean, bad, bed, quality, poor, limited, suffer, terrible, aircraft, leg, flat, seat_bed, old_plane, recline
F7	1.255	Bag, delay, luggage, day, arrive, check, get, told, hour, customer, information, airline, cancel, airport, connection, miss, travel, wait, customer_service, time, board, suffer, worst
Low cost airline passengers		
F8	2.503	Leg, seat, leg_room, room, comfort, plane, price, low, leg_space, space, expect, paid, choose, book, get, limit, uncomfortable, flight_seat
F9	1.909	Connect, delay, connecting_flight, unprofessional, avoid, customer, provide, total, airline, layover, customer_service, flight_delay, spent, staff, delay_hour, time, miss_connection, late, service
F10	1.435	Flown, problem, expect, low, time, huge, mistake, different, life, airline, end, book, budget_airline, crew_member, budget, unfriendly, change, cabin_crew, sign, kid, believe, avoid
F11	1.391	Hour, late, cancel, flight_delay, wait, flight, day, service, minute, airport, experience, bad, arrive, crew, custom, poor, boarding, staff, customer_service, worst, information, communication
F12	1.320	Luggage, book, bag, charge, ticket, euro, service, paid, check, meal, online, full, busy, reserve, baggage, print, show, extra, hand, company, cost, seat

Economy Cabin passengers

- *Factor 1 (Uncomfortable seats and poor leg room):* The main words associated with this factor are; “legroom”, “uncomfortable”, “seat”. In this factor, insufficient leg room causes comfort problems which is the most important factor for dissatisfaction of economy passengers. Seat comfort is also found in Skytrax research among one of the top customer complaints (Skytrax, 2015).
- *Factor 2 (Baggage & flight disruptions):* Delays and cancellations have always been quite important issue for airlines. Passengers showed their level of dissatisfaction in the reviews, particularly for the delays resulted with missing connecting flights.
- *Factor 3 (Unprofessionalism of staff):* This factor mostly explains the lack of occupational competence of staff particularly cabin crew. The primary associated words are; “language_barrier”, “knowledge”, “require”.

- *Factor 4 (Poor service and food & beverages):* This factor is about overall customer service experience where prominently food & beverages-related complaints take place. "bad_service", "food", "dirty", "beer" are particular terms related to the factor.

Premium Cabin passengers

- *Factor 5 (Unprofessionalism of staff):* The main emphasis of this factor is on inappropriate staff attitudes towards passengers. This factor marginally differs from the label used for economy passengers.
- *Factor 6 (Uncomfortable seats and old aircraft):* Customer complaints that fall under this factor are about overall seat comfort and the interior ambience of aircraft. "Old", "seat", "plane", "interior", "recline" are the words related to the factor.
- *Factor 7 (Baggage & flight disruptions):* This factor corresponds to baggage and flight disruptions similar to F2 for the economy passenger.

Low-cost airline passengers

- *Factor 8 (Uncomfortable seats and poor leg room):* Legroom and uncomfortable are common words under this factor. Passengers main comfort issue is related to the lack of leg room.
- *Factor 9 (Flight disruptions):* Customer complaints clustering under this factor are mostly about the long waiting time at airports and missing connecting flights because of flight delays and cancellations. This can be seen in the associated terms; "Cancel", "hour", "flight_delay", "spent", "hour".
- *Factor 10 (Consistent poor service delivery):* This factor is related with the frustration of passengers in terms of having consistently poor service, particularly staff behaviours are the main reason for the complaints. "Problems", "expect", "avoid", "cabin_crew" are the terms that are associated with the factor.
- *Factor 11 (Poor customer care)* This factor is generally related to flight disruptions, but while the complaint is not related to the disruption itself, it is more about the ability of the airline in terms of providing passenger recovery services and keeping passengers informed. The particular words linked with the factor are; "Experience", "customer_service", "worst", "information", "communication".

- *Factor 12 (Extra or hidden charges):* Ancillary fees of LCCs can be very expensive especially if they are not purchased prior to travel that cause passenger dissatisfaction such as; seat selection, excess baggage, printing tickets.

7. Discussion

The findings show that passenger satisfaction and dissatisfaction attributes differ depending on airline flown or service class. Furthermore, it is found that their level of importance shows some differences. However, these attributes do not demonstrate dramatic differences. The fundamental differences that establish passenger satisfaction reveal from the delivery of core business/service values. Friendly and helpful staff, value and low price are the most important factors for economy, premium and low-cost passenger respectively (Table 1-2).

Primarily, FSNC economy passenger value a friendly and helpful approach from staff and they expect hassle-free customer experience throughout the different touch points. Air travel tends to be stressful and different from other forms of transport particularly due to the uncontrollability of aspects such as when to board, where to sit or when to exit airplane. Furthermore, passengers are subjected to rigid security checks, and the air travel environment may provoke anxious and angry behaviour from passengers due to long queues, flight disruptions and bad behaviour from other passengers (Bricker, 2005). Resulting from this, it is therefore not surprising that passengers are expecting a good customer experience and care. Finally, comfortable seats are another determinant of passenger satisfaction which is not unexpected when descending leg-room and seat comfort in the economy cabin is considered.

The results also confirm previous findings of Forgas et al. (2010) that monetary cost and service quality are the main attributes that make satisfaction for LCC passenger, professionalism of the staff is the key satisfaction attribute for FSNCs. LCCs were able to meet specific needs (service-price) of price-sensitive passengers in the past but there is a considerable shift in the passenger mix based on airline type as a result of changing customer behaviours and airlines (Cho and Min, 2018). An evolving business environment makes the lines between LCCs and FSNCs unclear since there is not always significant variation in ticket fares among business models due to increasing operational efficiency capabilities of FSNCs over time (Siering et al., 2018). LCC passengers still look for monetary value, which also confirms previous research by O'Connell and Williams (2005); and Rajaguru (2016). It is interesting that monetary value is not the only factor, as passengers also expect to have some customer service, particularly from staff.

The results show that attributes that drive passenger satisfaction based on service class do not show major differences. The fundamental difference between premium and economy passengers is that the premium passengers expect more value which is the most important feature for the premium passenger. Park (2007) also found that the business passenger rates value for money higher than the economy passenger. The trade-off between what is given and what is received, is quite important to satisfy premium passengers. Premium products of airlines are (usually) more expensive so it is likely that premium passengers have high expectation from an airline. Therefore, airlines need to meet these higher expectations. Different from economy passenger, premium passengers seek for premium service attributes such as good range of food and beverage options, and comfortable flat-bed seats together with a good in-flight entertainment for their money's worth.

As for customer dissatisfaction attributes, they are rather similar to each other. Mainly, seat comfort/legroom, flight disruptions and staff service are the main factors causing passenger dissatisfaction for FSNC economy and LCC passenger. According to Skytrax (2015), lost luggage, flight delays, and aircraft seats are the main sources of passenger complaints.

The differences among the attributes pertain to their business model. Baggage disruptions and food & beverages complaints are specific for economy passengers. Increasing costs and increasing competition force FSNCs, either to remove in-flight catering or to reduce the quality and/or quantity of meals which then translates into customer dissatisfaction. Whereas "extra charges" are generally LCC-specific factor causing dissatisfaction. LCCs have complicated ancillary fare rules which require to a passenger to spend the time to read. Transparency of this information differ from airline to airline, while only a small number of customers take time to read this information (Skytrax, 2015). These ancillaries can be a very expensive last minute purchase which causes excessive level of dissatisfaction.

There is marginal difference in attributes causing passenger dissatisfaction for premium and economy passenger. Seat and aircraft-related issues, unprofessional staff behaviour, baggage loss and delays are the common dissatisfaction reasons for each group. Poor service and catering is another dissatisfaction reason for economy passengers. However, their rankings differ in each group.

It is important to note that some of the dissatisfaction attributes like flight and baggage disruptions was not observed among the satisfaction attributes. This can be well explained by Kano et al. (1984)`s approach that on-time performance can be regarded as a “must-be” or hygiene category which is not seen as satisfaction attribute, but deficiency of on-time performance causes an excessive level of dissatisfaction. Additionally, staff attitudes which could be positioned as “one-dimensional feature” of air travel since Kano et al., (1984) states that when this features are met, they increase satisfaction proportionally. Staff service is observed as an important satisfaction and dissatisfaction attribute for all passenger groups. Specifically, for LCC passenger, extra charges cause dissatisfaction whereas the key satisfaction driver for LCC passenger is low-cost travel that could be regarded as “one dimensional” factor for LCC passenger since extra charges may increase the cost of travel significantly.

8. Conclusion

This research finds the key driving factors of passenger satisfaction and dissatisfaction and their differences among airline business models and service class through online generated customer reviews. By using a well-established mathematical text mining technique, factors leading to satisfaction and dissatisfaction that are hidden in unstructured textual data are revealed. Results demonstrate that the determinants and importance of customer satisfaction and dissatisfaction vary slightly based on airline business model and service class.

This research provides clear managerial and academic implications. In the academic sense, various service attributes are used in the airline customer behaviour research to measure service quality and passenger loyalty. Using large numbers of attributes to measure satisfaction through passenger surveys is likely to cause fatigue which may cause validity and reliability problems. Therefore, standardised set of attributes may not be relevant for different passenger segments and airline types. However, unlike the previous research, this research highlights only the key drivers that satisfy passenger and compare them among different passenger groups. These key attributes may be used by researchers to re-examine the customer value creation process or to test theoretical models to have better understanding of airline passenger behaviour. Furthermore, attributes creating dissatisfaction require to pay extra attention since not all of them directly establish satisfaction but their absence create dissatisfaction.

In practice, the analysis of online reviews can be used as a diagnostic tool by managers since customer feedback is important for airlines to improve services and products, and to take action regarding service failures. The analysis also provides the level of importance of these service attributes so airlines can allocate their resources accordingly. Online review analyses can provide a low-cost and reliable satisfaction assessment to airlines. This analysis and constantly monitoring passenger reviews may facilitate management of E-WOM (e-word-of-mouth) which is critical for airlines due to their impact on customers' airline choice. TripAdvisor reviews have been important for hotel and restaurant customer in terms of affecting their decision making. Although it is a relatively new platform for airlines, these reviews are likely to create E-WOM in terms of affecting passengers' airline choice. Airlines can also use this method to analyse their competitors' passenger feedbacks so that they can benchmark themselves against competitors in terms of passenger satisfaction, therefore, these reviews can be used for strategic marketing decisions against competitors. All in all, for airlines customer satisfaction can be established by focusing on and/or improving the attributes leading satisfactions and by providing improvement on the service attributes causing dissatisfaction thus they can guarantee their future customers and so revenue.

9. Limitations and Future Research Suggestions

Although this research provides a step towards the use of online textual data, it is important to highlight the limitations. The sample of reviews are collected only from TripAdvisor.com as representative platform, therefore our results are limited to one particular website. Furthermore, it is important to highlight that only reviews in English were considered for the analysis so the results of the analysis may not reflect views by passengers writing in other languages. Another limitation of this study is the methodology used for text mining. LSA does not consider sentence-level individual document meaning emerging from word order, it is an inherent limitation of bag-of-word analysis methods (Evangelopoulos, 2013). Lastly, although LSA is conducted through a range of systematic, statistical analyses, human involvement takes place in the interpretation and factor labelling phase which poses subjectivity. This limitation is addressed by labelling factors by two independent researchers. Recommendation for future research would be to focus on satisfaction and dissatisfaction attributes for short-haul and long-haul passenger and examination of satisfaction and dissatisfaction attributes on a country level to see how these attributes differ. It would also be interesting to conduct LSA analysis to different online customer generated reviews such as Skytrax, Twitter and Facebook, as well as comparing the results of different websites.

Appendix A

Frequently Used Airline Service Attributes

Services Attributes	**ACSI**	**IATA(Airs@t)**	**Literature**
Reservation		Number of Attributes	
Flight schedule	✓		Ahn et al., 2015; Medina-Muñoz et al., 2018; Vlachos and Lin, 2014; Chen and Chao, 2015; Kim and Park, 2017
Frequency			Vlachos and Lin, 2014
Direct-Connecting Flight			Chen and Chao, 2015; Kim and Park, 2017
Call centre	✓		
Website	✓	✓ (4)	Chen and Chao, 2015
Staff			
Flight attendant's attractiveness			Ahn et al., 2015; Kim et al., 2016
Service Performance			Ahn et al., 2015; Kim et al., 2016
Flight crew (courtesy, helpfulness and friendly)	✓	✓ (7)	Vlachos and Lin, 2014; Chen and Chao, 2015; Kim and Park, 2017
Professionalism of staff			Forgas et al., 2010
Assurance (Courtesy and knowledge)			Leong et al., 2015; Calisir et al., 2016; Rajaguru, 2016
Cabin/Aircraft			

Seat comfort	✓	✓ (6)	Medina-Muñoz et al., 2018; Forgas et al., 2010; Han et al., 2014; Chen and Chao, 2015; Kim and Park, 2017
Cabin (Interior)		✓ (7)	Vlachos and Lin, 2014; Han et al., 2014; Chen and Chao, 2015
In-flight baggage space			Medina-Muñoz et al., 2018; Kim and Park, 2017
Odour, temperature, air quality, noise			Han et al., 2014
Airline Tangibles			Suki, 2014; Kim et al., 2016; Kos Koklic et al., 2017; Leong et al., 2015; Calisir et al., 2016; Rajaguru, 2016
Aircraft type			Chen and Chao, 2015
Environment and facilities			Ahn et al., 2015
In-Flight entertainment	✓	✓ (11)	Ahn et al., 2015; Medina-Muñoz et al., 2018; Kim et al., 2016; Han et al., 2014; Chen and Chao, 2015
Ground			
On-Time arrival	✓	✓	Forgas et al., 2010; Suki, 2014; Vlachos and Lin, 2014; Chen and Chao, 2015
Baggage handling	✓	✓	Ahn et al., 2015; Medina-Muñoz et al., 2018; Chen and Chao, 2015
Boarding (Ground services)	✓	✓ (4)	Medina-Muñoz et al., 2018; Chen and Chao, 2015; Kim and Park, 2017
Check-In	✓	✓ (6)	Ahn et al., 2015
Airport			Forgas et al., 2010; Suki, 2014
Lounge		✓ (7)	Ahn et al., 2015
In-Flight			
Food and Beverages		✓ (7)	Ahn et al., 2015; Medina-Muñoz et al., 2018; Vlachos and Lin, 2014; Kim et al., 2016; Chen and Chao, 2015
Duty free items			Chen and Chao, 2015
Other			
Loyalty programs (FFP)	✓	✓ (4)	Ahn et al., 2015; Vlachos and Lin, 2014; Chen and Chao, 2015
Safety/Reliability			Medina-Muñoz et al., 2018; Forgas et al., 2010; Vlachos and Lin, 2014; Leong et al., 2015; Calisir et al., 2016; Rajaguru, 2016; Chen and Chao, 2015
Price			Medina-Muñoz et al., 2018; Forgas et al., 2010; Vlachos and Lin, 2014; Calisir et al., 2016; Chen and Chao, 2015
Reputation			Vlachos and Lin, 2014; Calisir et al., 2016; Chen and Chao, 2015
Empathy			Leong et al., 2015; Calisir et al., 2016; Rajaguru, 2016
Responsiveness			Leong et al., 2015; Calisir et al., 2016; Rajaguru, 2016; Chen and Chao, 2015
Communication			Chen and Chao, 2015
Additional Charges			Kim and Park, 2017

Source: American Customer Satisfaction Index (ACSI, 2018)*, Airs@t (International Air Transport Association Passenger Satisfaction benchmarking survey)*(IATA, 2018a).

Appendix B

The list of airlines and the number of reviews collected.

	Country	Airlines	Busines Model	Number of Reviews		Country	Airlines	Busines Model	Number of Reviews
1	USA	American Airlines	FSC	100	26	Hong Kong	Cathay Pacific	FSC	103
2	USA	Delta	FSC	100	27	New Zeeland	Air New Zealand	FSC	104
3	USA	United Airlines	FSC	103	28	Taiwan	Eva Airways	FSC	104
4	USA	Southwest Airlines	LCC	100	29	South Korea	Asiana Airlines	FSC	102
5	Canada	Air Canada	FSC	105	30	Taiwan	China Airlines	FSC	102
6	USA	Alaska Airlines	FSC	96	31	Australia	Jetstar	LCC	102
7	USA	Jetblue Airways	LCC	98	32	Australia	Virgin Australia	FSC	101
8	Canada	Westjet Airlines	LCC	104	33	UK	British Airways	FSC	103
9	USA	Spirit Airlines	LCC	98	34	Germany	Lufthansa	FSC	106
10	USA	Hawaiian	FSC	97	35	Turkey	Turkish Airlines	FSC	102
11	UAE	FlyDubai	LCC	91	36	Ireland	Ryanair	LCC	106
12	UAE	Emirates	FSC	107	37	France	Air France	FSC	106
13	Qatar	Qatar Airways	FSC	105	38	UK	Easyjet	LCC	102
14	UAE	Etihad Airways	FSC	102	39	Russia	Aeroflot	FSC	106
15	Saudi Ara	Saudia	FSC	99	40	Norway	Norwegian Air	LCC	106
16	China	China Southern China	FSC	103	41	Netherlands	KLM	FSC	105
17	China	China Eastern China	FSC	104	42	Spain	Iberia	FSC	106
18	China	Air China	FSC	104	43	Switzerland	Swiss	FSC	104
19	Japan	ANA Japan	FSC	103	44	Sweden	Scandinavian Airline	FSC	104
20	Japan	Japan Airlines	FSC	100	45	Hungary	Wizz Air	LCC	102
21	Australia	Qantas	FSC	104	46	UK	Virgin Atlantic	FSC	106
22	Korea	Korean Air Lines	FSC	101	47	Chilie	LATAM	FSC	106
23	Singapor	Singapore Airlines	FSC	104	48	Mexico	Aeromexico	FSC	101
24	Thailand	Thai Airways	FSC	102	49	Colombia	Avianca	FSC	103
25	Malaysia	Airasia	LCC	98	50	Ethiopia	Ethiopian	FSC	100

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