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ARAŞTIRMA MAKALESİ / RESEARCH ARTICLE

EVALUATION OF CUSTOMER SATISFACTION DIMENSIONS IN FULL SERVICE AND LOW-COST AIRLINES VIA DYNAMIC TOPIC MODELING APPROACH

TAM HİZMET SUNAN VE DÜŞÜK MALİYETLİ HAVAYOLLARINDA MÜŞTERİ TATMİN BOYUTLARININ DİNAMİK KONU MODELLEME YAKLAŞIMI İLE DEĞERLENDİRİLMESİ

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ABSTRACT

The study aims to uncover the dimensions of customer satisfaction for full-service and low-cost airlines and examine the changes in these dimensions between 2015 and 2022. A total of 32,000 online customer reviews obtained from TripAdvisor are analyzed using BERTopic, a topic modelling method that facilitates the extraction of contextual information. The analysis reveals that the prominent dimensions of customer satisfaction for full-service airlines include baggage, flight delays, cabin crew, and in-flight services, while for low-cost airlines, price, COVID-19-related issues, and auxiliary services are emphasized. According to the results of dynamic topic modelling, negative reviews regarding cabin crew have increased for full-service airlines, whereas reviews related to in-flight entertainment have decreased. For low-cost airlines, reviews concerning flight cancellations and customer service have surged during the COVID-19 pandemic. These findings provide strategic recommendations to the industry by identifying key service areas affecting customer satisfaction and illustrating how customer feedback has evolved over time. The study offers valuable insights for managing long-term customer satisfaction in the airline industry.

Keywords: Customer Satisfaction, Airline Service Attributes, Text Mining, Dynamic Topic Modeling.

JEL Classification Codes: M30, M31, Z32.

ÖZ

Bu araştırma tam hizmet sunan ve düşük maliyetli havayollarına yönelik müşteri tatmin boyutlarını ortaya çıkararak bu boyutların 2015-2022 yılları arasındaki değişimlerini incelemeyi hedeflemektedir. TripAdvisor'dan elde edilen 32,000 çevrimiçi müşteri değerlendirmesi bağlamsal bilgilerin elde edilmesine olanak tanıyan bir konu modelleme yöntemi olan BERTopic ile analiz edilmiştir. Analiz sonucunda, tam hizmet sunan havayollarında öne çıkan müşteri tatmin boyutları arasında bagaj, uçuş gecikmeleri, kabin ekibi ve kabin içi hizmetler yer alırken, düşük maliyetli havayollarında fiyat, COVID-19 ile ilgili konular ve yardımcı hizmetler öne çıkmıştır. Dinamik konu modelleme sonuçlarına göre, tam hizmet sunan havayollarında kabin ekibi ile ilgili olumsuz değerlendirmeler artarken, kabin içi eğlenceye ilişkin değerlendirmelerin azaldığı belirlenmiştir. Düşük maliyetli havayollarında ise COVID-19 süreciyle birlikte uçuş iptalleri ve müşteri hizmetlerine yönelik değerlendirmelerde artış görülmüştür. Bu bulgular, hem müşteri tatminine yönelik önemli hizmet alanlarını belirleyerek sektöre stratejik öneriler sunmakta hem de müşteri geri bildirimlerinin zaman içinde nasıl evrildiğini göstermektedir. Çalışma, havayolu sektöründe uzun vadeli müşteri tatmini yönetimi için değerli sonuçlar ve çıkarımlar sağlamaktadır.

Anahtar Kelimeler: Müşteri Tatmini, Havayolu Hizmet Özellikleri, Metin Madenciliği, Dinamik Konu Modelleme.

JEL Sınıflandırma Kodları: M30, M31, Z32.

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GENİŞLETİLMİŞ ÖZET

Amaç ve Kapsam:

Bu araştırmanın amacı, tam hizmet sunan ve düşük maliyetli havayollarına ilişkin müşteri tatmin boyutlarını ortaya çıkarmak ve bu boyutların zaman içerisindeki değişimlerini incelemektir. Havayolu sektöründe müşteri tatminine yönelik artan ilgi ve çevrimiçi değerlendirme platformlarının yaygınlaşması, müşteri geri bildirimlerinin daha derinlemesine analiz edilmesine olanak sağlamaktadır. Bu bağlamda, çalışmada çevrimiçi müşteri değerlendirmeleri konu modelleme yöntemi kullanılarak analiz edilmiştir. Aynı zamanda tam hizmet sunan ve düşük maliyetli havayollarında öne çıkan müşteri tatmin boyutları belirlenmiş ve zaman içindeki değişimleri dinamik konu modelleme aracılığıyla incelenmiştir. Araştırma kapsamında, her iki iş modeli için belirlenen müşteri tatmin boyutlarının, hem müşteri tatmininde öne çıkan havayolu hizmetlerini anlamada hem de sektör yöneticilerine uzun vadeli stratejik kararlar almada rehberlik etmesi beklenmektedir.

Yöntem:

Tam hizmet sunan ve düşük maliyetli havayollarına ilişkin toplam 32,000 çevrimiçi müşteri değerlendirmesi araştırmanın veri kaynağını oluşturmaktadır. Veriler TripAdvisor platformundan web kazıma yöntemi kullanılarak elde edilmiştir. Elde edilen verilere çeşitli metin ön işleme adımları uygulanarak analize uygun hale getirilmiştir. Havayollarında müşteri tatmin boyutlarını belirlemek amacıyla konu modelleme yöntemi olarak güncel ve derin öğrenme tabanlı bir yöntem olan BERTopic tercih edilmiştir. Yöntem kapsamında ön eğitimli dil modelleri yardımıyla doküman düzeyinde temsiller oluşturulabilmektedir. Dolayısıyla geleneksel konu modelleme yöntemlerine bağlamsal olarak daha tutarlı bilgiler elde edilebilmektedir. Tam hizmet sunan ve düşük maliyetli havayolları için konu modelleme uygulamaları gerçekleştirilmiş ve her iki iş modeli için öne çıkan 10 müşteri tatmin boyutu belirlenmiştir. Müşteri tatmin boyutları belirlenirken her bir boyutu temsil eden en yüksek skora sahip ifadeler dikkate alınmıştır. Son aşamada ise dinamik konu modelleme yaklaşımı kullanılarak, elde edilen müşteri tatmin boyutlarının 2015-2022 yılları arasındaki değişimi ortaya konulmuştur.

Bulgular:

Tam hizmet sunan havayollarına ilişkin konu modelleme uygulaması sonucu 153 konu elde edilmiş, konu benzerlikleri ve konular arası uzaklıklar iki boyuttu düzlemde görselleştirilmiştir. Öne çıkan müşteri tatmin boyutları ise sırasıyla bagaj, yiyecek ve içecek, uçuş gecikmeleri, kabin ekibi (pozitif), koltuk, kabin içi hizmetler, kabin içi eğlence, uçuş iptalleri, kabin ekibi (negatif) ve müşteri hizmetleri olarak belirlenmiştir. Müşteri tatmininin büyük oranda uçuş aksaklıkları ve kabin hizmet faktörlerinde yoğunlaştığı görülmektedir. Düşük maliyetli havayollarına ilişkin müşteri değerlendirmelerinin analiz edilmesi sonucu ise 115 konu elde edilmiştir. Tam hizmet sunan havayollarına benzer şekilde konu benzerlikleri ve konular arası uzaklıklar iki boyuttu düzlemde görselleştirilmiştir. Düşük maliyetli havayollarında müşteri tatmin boyutları sırasıyla kabin ekibi (pozitif), uçuş iptalleri, müşteri hizmetleri, kabin içi hizmetler, tekerlekli sandalye ve yardımcı hizmetler, fiyat, koltuk, kabin ekibi (negatif), uçuş gecikmeleri ve COVID-19 ile ilgili konular olarak belirlenmiştir. Tam hizmet sunan havayollarıyla ortak faktörlerin yanı sıra fiyat, yardımcı hizmetler ve COVID-19 sürecine özgü faktörlerin müşteri tatmini ile önemli derecede ilişkili olduğu görülmüştür. Bunun yanı sıra tam hizmet sunan havayollarında 2015-2022 yılları arasında bagaj, uçuş gecikmeleri, uçuş iptalleri, kabin ekibi (olumsuz) ve müşteri hizmetleriyle ilgili müşteri değerlendirme sayısının arttığı, buna karşın kabin ekibi (olumlu), koltuklar ve uçak içi eğlenceye yönelik değerlendirmelerin azaldığı gözlemlenmiştir. Düşük maliyetli havayollarında ise aynı zaman diliminde uçuş gecikmeleri, müşteri hizmetleri, kabin ekibi (negatif) ve COVID-19 ile ilgili konulara ilişkin müşteri değerlendirmelerinin arttığı söylenebilmektedir.

Sonuç ve Tartışma:

Tam hizmet sunan havayolları için elde edilen müşteri tatmin boyutları Atalık (2007), Forgas vd. (2010), Kos Koklic vd. (2017) gibi çalışmalarla büyük ölçüde benzerlik göstermektedir. Bunun yanında önceki araştırmalarda benzer boyutların farklı isimlerle tanımlandığı ya da araştırma kapsamında elde edilen boyutların literatürde yer alan belirli hizmet özelliklerini kapsadığı görülmektedir. Ek olarak literatürdeki birçok benzer bulgunun, fiziksel özellikler ve yanıt verebilirlik gibi boyutları kategorize eden SERVQUAL gibi modeller çerçevesinde ele alındığı görülmektedir. Ayrıca diğer çalışmalarda vurgulanan "seyahat türü" ve "sık uçan yolcu programı" gibi boyutlar bu araştırmada öne çıkan müşteri tatmin boyutları arasında yer almamaktadır. Dinamik konu modelleme uygulaması sonucunda yiyecek ve içecek ile kabin içi eğlence gibi kabin içi hizmet faktörlerinin yıllar içerisinde önemini koruduğu ancak kabin ekibi ile ilgili yorumlarda ise olumsuz unsurların yıllar içinde daha belirgin hale geldiği gözlemlenmiştir. Düşük maliyetli havayollarında seyahat eden yolculara ilişkin elde edilen bulgular büyük ölçüde Bakır vd. (2019), Forgas vd. (2010), Kim ve Lee (2011) ve Sezgen vd. (2019)'u desteklemektedir. Ancak geçmiş çalışmalarda ortaya konulan temizlik, yiyecek ve içecekler ile havaalanı prosedürleri gibi boyutlar bu bulgular arasında yer almamaktadır. Ayrıca tekerlekli sandalye ve yardım hizmetleri ile COVID-19 ile ilgili konular bu çalışmada tespit edilen literatürden farklılık gösteren boyutları oluşturmaktadır. Müşteri yorumlarında vurgulanan konuların, özellikle COVID-19 pandemisi sırasında ve sonrasında değiştiği dikkat çekmektedir. 2019'dan itibaren uçuş iptalleri ve müşteri hizmetlerine yönelik yorumların artışı, pandeminin neden olduğu uçuş aksaklıklarıyla ilişkilendirilmektedir. Ancak önceki çalışmalarda da vurgulandığı gibi, krizlerin dışında dahi uçuş gecikmeleri ve iptalleri müşteri tatminini doğrudan etkilemektedir.

1. INTRODUCTION

The airline transportation industry is a sector where companies operate amidst various challenges in a highly competitive environment. Airlines strive to cope with fluctuating fuel prices, economic crises, natural disasters, and pandemics, while also meeting the highly diverse service demands of passengers (Calisir et al., 2016). Maintaining high levels of passenger satisfaction is considered a crucial factor for airlines to achieve a competitive edge. Consequently, identifying the key dimensions that contribute to passenger satisfaction with airline services is of great importance. (Chen, 2008; Park et al., 2004).

Activities aimed at measuring customer satisfaction provide various benefits to businesses. By examining the extent to which their services meet customer expectations, businesses can identify competitive advantages based on customer perceptions. Additionally, analyzing the impact of business operations on customers plays a crucial role in determining the dimensions of customer satisfaction that require improvement (Lucini et al., 2020).

The interaction between service quality and customer satisfaction is often non-linear, which complicates the evaluation of customer satisfaction. In the literature, various approaches have been adopted to evaluate the dimensions of airline service quality and customer satisfaction. While certain studies have utilized statistical techniques such as regression analysis to model the relationship between service quality and customer satisfaction (Ali et al., 2016; Josephat & Ismail, 2012), others have applied Multi-Criteria Decision-Making (MCDM) methods to assess and enhance service quality (Li et al., 2017; Liou et al., 2011). In addition to quantitative methods, qualitative and mixed-method approaches have also been utilized by researchers to identify the dimensions of customer satisfaction (Guo et al., 2017). However, factors such as limited sample sizes, inconsistencies in the scales used, and the possibility that customers may not always take survey studies seriously can lead to misleading results (Lucini et al., 2020; Wan & Gao, 2015).

In recent years, alongside traditional methods, online content generated by customers has been increasingly utilized to understand customer expectations and preferences. Customers can directly share their evaluations of experiences across various online platforms (Chau & Xu, 2012). By analyzing large volumes of reviews using artificial intelligence and text mining techniques, businesses and researchers can gain new insights into service quality and customer satisfaction (Lucini et al., 2020). Examining customer-generated reviews through these methods offers a distinct and complementary approach to traditional research. The open-ended nature of reviews, their potential to reach a large audience, and the anonymity of reviewers provide a more comprehensive understanding of customer satisfaction (Xu et al., 2017). Additionally, these methods avoid common issues associated with traditional measurement tools. However, the effectiveness of text mining methods in evaluating customer opinions is often limited. For example, Latent Dirichlet Allocation (LDA), a commonly used topic modeling method for identifying themes in textual data, is unable to account for word order and the contextual information that arises from sentence structure. (Abuzayed & Al-Khalifa, 2021; Lucini et al., 2020). The recent advancements in artificial intelligence technologies have led to the emergence of deep learning models, which are more effective in capturing contextual information. In traditional topic modeling approaches, the bag-of-words representation disregards semantic relationships between words. To address this issue, document representation methods are rapidly gaining popularity in the field of natural language processing (Egger & Yu, 2022). Within this framework, the BERTopic method, which utilizes pre-trained language models to generate document embeddings, was applied in this study to identify the dimensions of customer satisfaction. Furthermore, the dynamic topic modeling approach facilitated by this method was employed to analyze the temporal evolution of customer satisfaction dimensions, and the underlying causes of these changes were explored (Grootendorst, 2022).

The research aims to answer the following two questions:

RQ1: What are the prominent dimensions of customer satisfaction in full-service and low-cost airlines?

RQ2: How have the dimensions of customer satisfaction in full-service and low-cost airlines changed between 2015 and 2022?

2. LITERATURE REVIEW

Customer satisfaction is a crucial concept in marketing, as it is a significant determinant of repurchase behavior, word-of-mouth communication, and customer loyalty (Ryu & Han, 2010). One of the early researchers in this field, Cardozo (1965), demonstrated that customer satisfaction with products promotes both repurchase behavior and positive word-of-mouth communication. Similarly, Oliver (2010) argues that achieving high levels of customer satisfaction is essential for ensuring repeat purchases and sustaining business profitability. Therefore, businesses must not only focus on preventing customer dissatisfaction but also on enhancing satisfaction levels (Oliver, 2010). As a result of this approach, the concept of customer satisfaction has garnered increasing attention from both researchers and businesses in recent decades (Rust & Oliver, 1994).

Several theories have been proposed in the literature to explain the concept of customer satisfaction. However, one of the most widely accepted theories for explaining the relationship between customer expectations and perceived business performance is the Expectation Disconfirmation Theory. This theory suggests that customer satisfaction or dissatisfaction with a product is determined by comparing the expectations prior to consumption with the perceived performance levels experienced after consumption (Oliver, 2010). According to Oliver (2010), before purchasing a good or service, customers form certain expectations about its attributes. If the perceived performance of the product after consumption matches or exceeds the expected performance, it is assumed that the customer will be satisfied, resulting in confirmation. Conversely, if the expected performance falls short of or exceeds the perceived performance, it is assumed that the customer will be dissatisfied, leading to disconfirmation. This disconfirmation is classified as either positive or negative, depending on the extent of the mismatch between expected and perceived performance (Churchill & Surprenant, 1982). Though the literature lacks a universally accepted definition of customer satisfaction, the concept is commonly defined as the customer's evaluation of a product's performance in comparison to their expectations. Additionally, the definition of customer satisfaction may vary across different industries. Within the airline industry, customer satisfaction can be defined as the degree to which passengers' expectations align with the actual performance of airline services. Therefore, in airlines, customer satisfaction is influenced by both customer needs and expectations, as well as the specific characteristics of the airline's services (Sánchez-Rebull et al., 2018).

Given the dynamic nature of the industry, defining airline business models using a standardized formula and classifying airlines based on their business models is challenging (Mason & Morrison, 2008). However, from a customer perspective, pre-purchase expectations and post-consumption perceptions of airline services can vary depending on the product and service distinctions related to the airline's business model. As a result, passengers may develop different expectations for low-cost carriers (LCCs) and full-service carriers (FSCs), and these expectations can lead to satisfaction or dissatisfaction based on the airline's service performance (Sezgen et al., 2019).

The rivalry between full-service carriers (FSCs) and low-cost carriers (LCCs) in the global airline market is progressively intensifying over time (Han & Hwang, 2017). Particularly in emerging markets, LCCs focus on cost-reduction strategies to attract cost-sensitive passengers, thereby increasing their market share (Kua & Baum, 2004; Martinez-Garcia & Royo-Vela, 2010). In contrast, FSCs aim to gain a competitive advantage by concentrating on hub airports, rather than the point-to-point flight strategy employed by LCCs, and by providing high-quality service to maintain customer loyalty (Dennis, 2007). In this competitive environment, it is crucial to understand the characteristics of different business models and the variations in service quality perceptions between FSC and LCC customers in order to differentiate service strategies and gain a competitive edge (Kos Koklic et al., 2017; Lee et al., 2018). The key differences between business model characteristics are outlined in Table 1 (Baker, 2013; O'Connell & Williams, 2005):

Table 1. Key Differences Between Business Model Characteristics

Feature	Low-Cost Carrier	Full-Service Carrier
Brand	Single brand: Low price	Extended brand: price/service
Pricing	Simple pricing	Complex pricing
Distribution	Direct, online	Direct, online, travel agencies
Check-in	Kiosk, e-ticket	Kiosk, e-ticket, paper ticket
Network	Point-to-point	Hub-and-spoke network
Cabin Class	Single class	Multiple classes
In-flight Service	No complimentary service	Complimentary services
Aircraft Utilization	Highly intensive	Moderate to intensive

Feature	Low-Cost Carrier	Full-Service Carrier
Aircraft Type	Single Type	Various Types
Turnaround Time	Short	Longer: congestion/complexity
Customer Service	Generally low performance	Generally reliable
Airports	Secondary airports	Primary airports
Operational Focus	Primarily passenger	Passenger, cargo
Target Customers	Price and time-sensitive passengers	Business and leisure passengers
Services	No frequent flyer program or lounges	Frequent flyer program and lounges

As seen in Table 1, FSCs offer a range of services, including high-frequency flight schedules, extensive in-flight entertainment, complimentary catering services, and a network structure that supports connecting flights (Nejati et al., 2009; Pakdil & Aydın, 2007). LCCs, on the other hand, have reshaped the competitive landscape in liberalized markets through the low prices they offer, particularly making a significant impact on the domestic market (O'Connell & Williams, 2005). The key factor behind the success of LCCs is their competitive pricing advantage (Goodrich, 2002). The different strategies pursued by airlines result in variations in the services provided. Numerous studies in the literature have frequently examined customer perceptions of airline service quality, revealing significant differences in service features between LCCs and FSCs.

Atalık (2007) conducted a study examining common complaints from frequent flyers of Turkish Airlines, identifying five key service quality factors: deficiencies in complimentary tickets and upgrades, staff behavior, issues related to card usage (such as the high number of flight miles required to maintain membership), the level and quality of priority services offered within the frequent flyer program, and shortcomings related to airline alliances (Atalik, 2007). Similarly, a study by Pakdil and Aydın (2007) analyzed Turkish Airlines customers' perceptions of service quality, finding that the "responsiveness" dimension was the most important, while "accessibility" was the least important service quality factor. The study also demonstrated a significant relationship between service quality and customer satisfaction (Pakdil & Aydın, 2007). In another study, Nadiri et al. (2008) found that, for customers of the national carrier in Northern Cyprus, the "physical attributes" dimension of service quality had the greatest influence on customer satisfaction and repurchase intention (Nadiri et al., 2008). Kim and Lee (2011), investigating the satisfaction of passengers using low-cost airlines in South Korea, employed the SERVQUAL scale to measure perceptions of service quality. Their findings indicated that the "physical attributes" and "responsiveness" dimensions were the most important determinants of customer satisfaction among the five SERVQUAL dimensions (Kim & Lee, 2011).

Forgas et al. (2010) conducted a study examining three airlines operating on the same route in Europe, aiming to identify the antecedents of customer loyalty for passengers traveling with both FSCs and LCCs. The study revealed that customer satisfaction and trust are significant predictors of customer loyalty in both business models. However, the antecedents of customer satisfaction were found to differ significantly based on the airline type. For LCC passengers, service quality and price were the primary drivers of satisfaction, whereas for FSCs, the professionalism of the staff was the main factor (Forgas et al., 2010). Similarly, Rajaguru (2016) investigated the effects of price-value ratio and service quality on customer satisfaction and behavioral intentions for FSC and LCC customers. The study found that for LCC passengers, the price-value ratio was the primary determinant of satisfaction and behavioral intentions. In contrast, for FSC passengers, a balance between price-value ratio and service quality was crucial (Rajaguru, 2016). Kos Koklic et al. (2017) found a strong positive relationship between customer satisfaction and factors such as staff quality, seat comfort, legroom, and additional services for FSCs, highlighting the importance of airline physical attributes (Kos Koklic et al., 2017).

Researchers and practitioners typically rely on traditional quantitative, qualitative, and mixed research methods to define and measure customer satisfaction dimensions (Guo et al., 2017). However, with the increasing interaction of customers sharing their opinions and experiences on online platforms such as Facebook, Twitter, and Skytrax, a large amount of valuable data has become available to airlines and researchers. The effective analysis of this unstructured data through text mining methods allows for the real-time evaluation of customer feedback, in contrast to traditional methods (Yee Liau & Pei Tan, 2014). In recent years, there has been a notable increase in text mining studies examining service quality and customer satisfaction within the airline industry, mirroring trends observed in other sectors, with the aim of gaining deeper insights into customer preferences and behaviors (Korfiatis et al., 2019; Lucini et al., 2020; Sezgen et al., 2019).

Yee Liau and Pei Tan (2014) analyzed customer opinions to better understand the needs of passengers flying with low-cost carriers in Malaysia. They applied sentiment analysis and clustering analysis to 10,895 Twitter posts. Both clustering methods highlighted key issues such as customer service, ticket promotions, flight cancellations/delays, and reservation management. While customer service and reservation management topics showed a mix of positive and negative emotions, flight cancellations/delays elicited mostly negative emotions, and ticket promotions were associated with neutral emotions (Yee Liau & Pei Tan, 2014).

Sezgen et al. (2019) examined the key determinants of passenger satisfaction and dissatisfaction using a topic modeling method called Latent Semantic Analysis (LSA). They analyzed 5,120 TripAdvisor reviews, consisting of 2,584 positive and 2,536 negative reviews from passengers traveling in economy, premium, and low-cost airlines. The study found that low-cost airline satisfaction was primarily driven by low prices, helpful staff, and cabin crew service, while dissatisfaction stemmed from seat discomfort, flight delays/cancellations, consistently poor service, poor customer service, and additional fees (Sezgen et al., 2019).

Lim and Lee (2020) conducted a comparative analysis of passenger perceptions of service quality in full-service carriers (FSCs) and low-cost carriers (LCCs). They analyzed 11,031 Skytrax reviews (7,462 for FSCs and 3,569 for LCCs) using Latent Dirichlet Allocation (LDA), a common topic modeling method, identifying 27 topics. These topics were matched with the five dimensions of the SERVQUAL model. The study found that physical attributes and reliability were the most important service dimensions for both FSCs and LCCs, while assurance and empathy were the least important. Additionally, sentiment analysis showed that LCC passengers exhibited fewer negative emotions compared to FSC passengers (Lim & Lee, 2020).

Lucini et al. (2020) analyzed 55,775 Skytrax reviews from over 400 airlines to explore customer satisfaction dimensions. Using LDA, they identified 27 customer satisfaction dimensions, including customer service, catering, cabin service, delays, and seating. The findings indicated that the cabin service class had the greatest impact on satisfaction, while passenger type had the least impact (Lucini et al., 2020).

Kwon et al. (2021) analyzed more than 14,000 online passenger reviews from 27 airlines on the Skytrax platform to identify important topics in the reviews. Using word frequency analysis, topic modeling, and sentiment analysis, the study identified seating, service, and catering as key topics. The sentiment analysis further revealed that delays were the primary source of customer dissatisfaction, while staff service was the main factor driving customer satisfaction (Kwon et al., 2021).

In addition to the findings from these studies, Table 2 summarizes key research on airline service quality and customer satisfaction, along with the dataset sizes and methods used.

Table 2. Datasets and Methods Used in Key Text Mining Studies on Airline Service Quality and Customer Satisfaction

Author	Data Source	Dataset Size	Method
Misopoulos et al. (2014)	Twitter	67,953	Sentiment Analysis, Frequency Analysis
Yee Liau & Pei Tan (2014)	Twitter	10,895	Clustering Analysis, Sentiment Analysis
Xu & Li (2016)	Skytrax	1,120	Topic Modeling
Bogicevic et al. (2017)	Skytrax	901	Visual Data Mining, Logistic Regression
Punel & Ermagun (2018)	Twitter	1,934	Network Analysis, Clustering Analysis
Stamolampros et al. (2018)	TripAdvisor	557,208	Topic Modeling, Regression Analysis
Ban et al. (2019)	Skytrax	2,222	Network Analysis
Brochado et al. (2019)	TripAdvisor	1,200	Content Analysis
Hong & Park (2019)	Skytrax	411	Word Extraction, Clustering Analysis
Korfiatis et al. (2019)	TripAdvisor	557,208	Topic Modeling
Kumar & Zymbler (2019)	Twitter	120,766	SVM, ANN, CNN, Sentiment Analysis
Nam & Lee (2019)	TripAdvisor	41,959	Topic Modeling, Sentiment Analysis
Park et al. (2019)	Online Survey	133,872	Sentiment Analysis, Structural Equation Modeling (SEM)

Author	Data Source	Dataset Size	Method
Punel et al. (2019)	Skytrax	40,510	Sentiment Analysis, Frequency Analysis
Sezgen et al. (2019)	TripAdvisor	5,120	Topic Modeling
Kim et al. (2020)	Skytrax	3,573	Network Analysis
Lim & Lee (2020)	Skytrax	11,031	Topic Modeling, Sentiment Analysis
Lucini et al. (2020)	Skytrax	55,775	Topic Modeling, Regression Analysis
Park et al. (2020)	TripAdvisor	157,035	Regression Analysis
Shadiyar et al. (2020)	Skytrax	1,693	Network Analysis, Regression Analysis
Seo & Itoh (2020)	Skytrax	6,393	Sentiment Analysis, Regression Analysis
Tian et al. (2020)	Twitter	785,557	Sentiment Analysis
Abdullah et al. (2021)	Twitter	14,641	Feature Extraction, ANN, Sentiment Analysis
Kwon et al. (2021)	Skytrax	>14,000	Frequency Analysis, Topic Modeling, Sentiment Analysis
Sulu et al. (2021)	TripAdvisor	498	Content Analysis
Chatterjee et al. (2022)	Skytrax	27,052	Sentiment Analysis, Structural Equation Modeling (SEM)
Sekar & Santhanam (2022)	TripAdvisor	9,574	Sentiment Analysis
Çallı & Çallı (2023)	ŞikayetVar	10,594	Topic Modeling
Park (2023)	Skytrax	22,377	Data Envelopment Analysis (DEA)

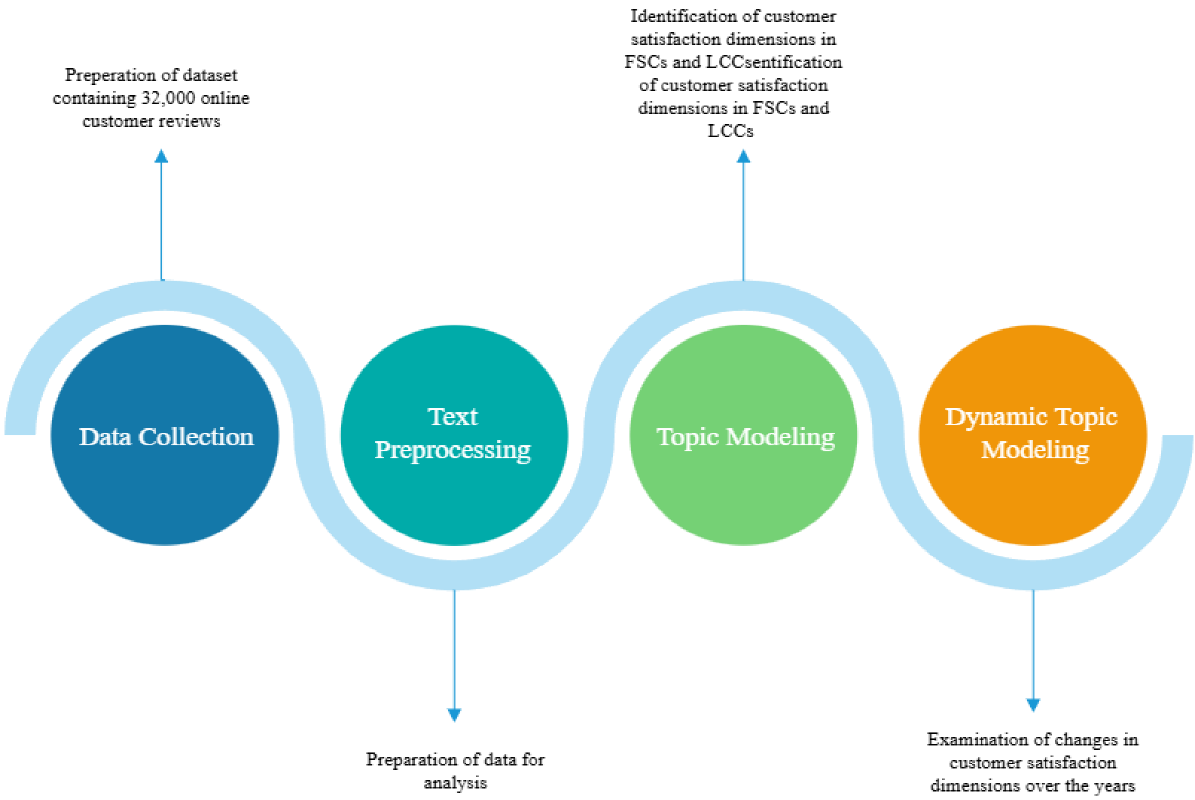
The use of topic modeling and sentiment analysis methods stands out in the literature on text mining studies related to airline service quality and customer satisfaction. Sentiment analysis applications focus on extracting emotions from passenger reviews by identifying key terms. In topic modeling applications, the main topics and themes that emerge from passenger reviews are identified. Most topic modeling studies utilize probabilistic methods such as Latent Dirichlet Allocation (LDA), which provide limited contextual information. However, recent advances in deep learning-based topic modeling methods allow for the generation of sentence-level representations using pre-trained language models, thereby enabling the extraction of more contextually coherent information. Despite these advances, only a limited number of studies have been identified in the literature that employ deep learning-based topic modeling approaches using pre-trained language models to examine airline service quality and customer satisfaction. Therefore, the use of such methods in this research is expected to make a significant contribution to the literature.

3. METHOD

3.1. Research Model

The aim of this research is to uncover the dimensions of customer satisfaction by analyzing passenger reviews shared online through a text mining method, specifically topic modeling. In this context, reviews and related metadata from TripAdvisor, a platform where airline passengers can share their opinions about flights, were collected, focusing on airlines with different business models. The collected data were prepared for analysis through a text preprocessing process. In the next stage, the BERTopic topic modeling method was used to identify prominent topics in both full-service carriers (FSCs) and low-cost carriers (LCCs). The words representing these topics were labeled with the help of expert opinions and defined as dimensions of customer satisfaction. In the final stage, the changes in the prominent customer satisfaction dimensions over the years for both FSCs and LCCs were examined. The steps of the research process are presented in Figure 1.

Figure 1. Steps of the Research Process



3.2. Data Collection

In this study, secondary data obtained from the internet were used. To explore the dimensions of customer satisfaction among airline passengers, online passenger review data were collected from the TripAdvisor website (https://www.tripadvisor.com). TripAdvisor is a platform where people can write reviews and rate services provided by hotels, restaurants, airlines, and other businesses. Launched in 2000, the site now features over a billion user reviews in 22 languages (Tripadvisor Media Center, 2022). The primary reason for choosing TripAdvisor as the data source is that the content generated by users directly reflects customer satisfaction. Through online reviews, passengers can express elements they were either satisfied with or dissatisfied with regarding their flights. Additionally, there is unrestricted access to customer reviews on TripAdvisor, and many studies in the literature have utilized data obtained from this platform.

To define the study sample, similar text mining studies in the literature were reviewed, and 25 airlines with the highest revenue passenger kilometers (RPK) on a global scale, as reported by IATA, were selected (IATA, 2021). Customer reviews and metadata related to these selected airlines were collected from the TripAdvisor.com website to form the dataset. The determination of the business models for the selected airlines was based on the "Global Air Transport Outlook to 2030" report published by ICAO and other recent research in the literature (ICAO, 2022). The airlines examined in the study and their business models are presented in Table 3.

Table 3. The List of Airlines and Business Models

	Airline	Business Model
1	American Airlines	FSC
2	China Southern Airlines	FSC
3	Delta Air Lines	FSC
4	United Airlines	FSC
5	China Eastern Airlines	FSC
6	Southwest Airlines*	LCC
7	Emirates	FSC
8	Air China	FSC
9	Ryanair*	LCC
10	Qatar Airways	FSC
11	Turkish Airlines	FSC
12	Air France	FSC
13	LATAM	FSC
14	British Airways	FSC
15	IndiGo*	LCC
16	Lufthansa	FSC
17	Aeroflot Russian Airlines	FSC
18	Sichuan Airlines	FSC
19	KLM	FSC
20	Xiamen Airlines	FSC
21	Shenzhen Airlines	FSC
22	JetBlue*	LCC
23	Spirit Airlines*	LCC
24	Hainan Airlines	FSC
25	Alaska Airlines	FSC

Cross-sectional data consisting of passenger reviews from 2015 to 2022, based on the dates when passengers completed their flights, was used within the scope of this research. To ensure a more accurate analysis of the changes in the frequency of customer satisfaction dimensions over the years, random sampling was conducted to select an equal number of passenger reviews for each year, given the varying number of reviews collected for each airline. The distribution of passenger reviews according to the business model and years is presented in Table 4.

Table 4. The Distribution of Passenger Reviews by Business Model and Year

Full-Service Carrier		Low-Cost Carrier	
Year	**Number of Reviews**	**Year**	**Number of Reviews**
2015	2000	2015	2000
2016	2000	2016	2000
2017	2000	2017	2000
2018	2000	2018	2000
2019	2000	2019	2000
2020	2000	2020	2000
2021	2000	2021	2000
2022	2000	2022	2000
Total	16000	**Total**	16000

In the research, only passenger reviews written in English were considered. Due to the international nature of the aviation industry, a significant portion of the reviews related to the selected airlines were written in English. Thus, English reviews were preferred to obtain a larger dataset. Additionally, the preference for English reviews provides an advantage in terms of the topic modeling tools and language models that will be used in the data analysis.

3.3. Text Preprocessing

Text preprocessing, as a fundamental component of the text mining process, transforms raw textual data into a more manageable and homogeneous format, thus preparing the data for subsequent analysis. This stage is critical because inconsistencies, errors, and data-specific factors frequently present in the data can significantly reduce the accuracy and efficiency of the analysis models (Hotho et al., 2005). In the topic modeling method used in this research, BERTopic, the steps of text preprocessing can vary based on the specific needs of the analysis. Due to the use of document embeddings within this method, many standard preprocessing steps may not be necessary (Grootendorst, 2022). However, because the tools used in the analysis are case-sensitive, all text was converted to lowercase. Additionally, commonly used words in passenger reviews, such as stop words, as well as expressions including country, city, destination names, aircraft models, and airline names, which could negatively impact the findings, were identified and filtered out.

3.4. Topic Modeling

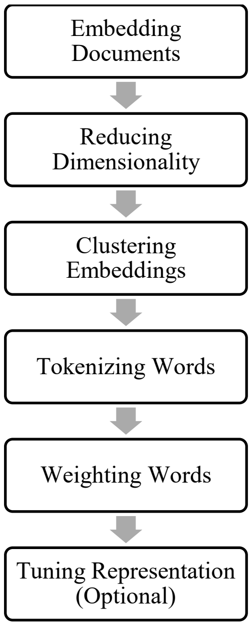
Topic modeling is a technique aimed at uncovering hidden structures or themes within a collection of documents. This method groups frequently co-occurring words and phrases into clusters known as topics. The extracted topics help summarize and organize large text datasets while providing a thematic overview of the content (Blei et al., 2003). Due to its ability to process large-scale datasets and reveal patterns that may be overlooked in manual analyses, topic modeling is becoming an increasingly popular technique in fields such as digital humanities, social sciences, and business analytics (Boyd-Graber et al., 2017).

It can be said that topic modeling methods have a wide range of applications. Researchers utilize topic modeling to identify key themes in scientific literature, allowing them to uncover gaps or emerging trends. This approach is particularly valuable in interdisciplinary research. In addition to researchers, businesses also employ topic modeling to analyze customer reviews, social media posts, and survey data to gain insights into customer perceptions and emerging market trends. Furthermore, news and media organizations use topic modeling to monitor public discourse, track evolving opinions over time, and analyze journalism across different platforms, illustrating the diverse applications of the method (Roberts et al., 2016).

The topic modeling method used in the research, BERTopic, is a topic modeling approach that leverages clustering techniques and a class-based TF-IDF variation to create semantically coherent topics using document representations. In this method, document embeddings are first generated by utilizing a pre-trained language model to extract document-level information. Then, the dimensionality of the document embeddings is reduced, and semantically similar document clusters are formed using a clustering algorithm. Finally, unlike the centroid-based approach in Top2Vec, BERTopic employs a class-based TF-IDF to reveal the words representing the topic (Grootendorst, 2022).

BERTopic workflow is illustrated in Figure 2:

Figure 2. Diagram of the BERTopic Workflow



Source: (Grootendorst, 2023).

As seen in Figure 2, in the first stage, Sentence-BERT (Reimers & Gurevych, 2019) is utilized to create contextual representations in vector space. In the subsequent step, the UMAP algorithm (McInnes et al., 2018) is employed to reduce the dimensions of these representations. The dimensionally reduced representations are then clustered using the HDBSCAN algorithm (McInnes et al., 2017), forming semantically similar document clusters. Following this, a class-based TF-IDF (c-TF-IDF) is applied to extract important words for each cluster. c-TF-IDF treats all documents within a cluster as a single document and applies TF-IDF, thus calculating the importance scores of words within the cluster. The words with high importance scores within the cluster represent the topic (Grootendorst, 2022; Koruyan, 2022). Moreover, the method allows for the optimization of topic representation generation using various models, such as GPT, T5, and KeyBERT, optionally (Grootendorst, 2023).

Some of the advantages of the BERTopic method are listed below (Egger & Yu, 2022; Grootendorst, 2022; Koruyan, 2022):

- The number of topics can be automatically determined.
- It is a modular method. Each processing step is independent, and different algorithms can be used to optimize the model at each step.
- It provides better results than traditional methods, such as LDA, particularly for short texts (Alhaj et al., 2022; Sánchez-Franco & Rey-Moreno, 2022).
- The method inherently supports various topic modeling variations, including dynamic, hierarchical, online, multimodal, and semi-supervised topic modeling.
- Similar to other methods utilizing document representations, there is no need for text preprocessing stages to be applied to the input data.
- It enables multilingual analysis through pre-trained language models that support more than 50 languages.
- Hierarchical topic reduction is supported.
- It includes built-in search functions for topics and documents.
- It has an integrated data visualization library, allowing for the visualization of the weight distributions of words related to a topic and the distances between topics in vector space.

In addition to its advantages, the method has the following limitations (Egger & Yu, 2022; Grootendorst, 2022):

- Due to the large number of topics that can be generated by the embedding approach, the resulting models may be more difficult to evaluate and interpret. To mitigate this issue, topic reduction techniques are recommended.
- Each document is associated with a specific topic.
- The method can produce a significant number of outliers, which may negatively affect the number of documents assigned to topics.
- Although there are various metrics in the literature, such as topic diversity and topic coherence, there are no objective criteria for evaluating the model comprehensively.
- The sequence length limitations of pre-trained language models can prevent the complete analysis of longer documents.
- Fine-tuning and selecting the optimal parameters for clustering and dimensionality reduction can be challenging and may require domain expertise or multiple iterations.

In the research, when selecting the pre-trained language model to be used for generating document embeddings, the performance scores of models available on the SBERT platform were compared, and the "all-mpnet-base-v2" model, which had the highest score, was chosen (SBERT, 2022). One of the key challenges in topic modeling methods is determining the optimal number of topics. Avoiding a model that is either too detailed or too general can require trial and expertise (Chang et al., 2009). Various approaches are discussed in the literature on this issue. Many studies utilize numerical criteria to determine the most appropriate number of topics (Rüdiger et al., 2022). However, some research suggests that numerical measures alone are insufficient, and better results can be achieved with human evaluation (Chang et al., 2009). Moreover, methods that combine both approaches to determine the optimal number of topics are also encountered (Jacobi et al., 2016). In the BERTopic method, the number of topics can be manually selected by the user or automatically determined by the algorithm. For this research, the number of topics was automatically determined, and the top 10 prominent topics were examined. These topics were named based on the top five most frequent words representing each topic, and customer satisfaction dimensions were identified.

To examine the changes in the customer satisfaction dimensions between 2015 and 2022, the top 10 emerging dimensions were analyzed using the dynamic topic modeling feature of BERTopic. Dynamic Topic Modeling (DTM) is a method that stands out for analyzing the evolution of latent themes in text collections over time. In this method, models are created for specific time periods in an interdependent manner, ensuring the continuity of topics. Therefore, DTM becomes particularly useful for capturing trends in time series data and predicting future trends (Blei & Lafferty, 2006). In the context of this research, passenger reviews were classified based on time labels, and changes over the years were analyzed.

4. RESULTS

4.1. Dimensions of Customer Satisfaction in FSCs

A topic modeling analysis was conducted to identify the dimensions of customer satisfaction for passengers traveling with full-service carriers (FSCs), resulting in the extraction of 153 topics. The similarities and distances between these topics are presented in the intertopic distance map, as illustrated in Figure 3.

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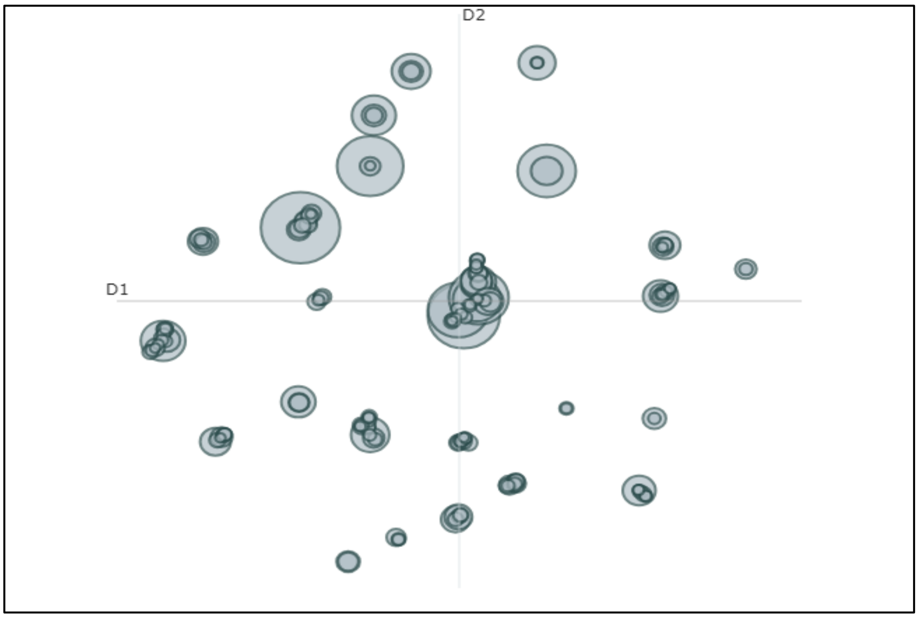
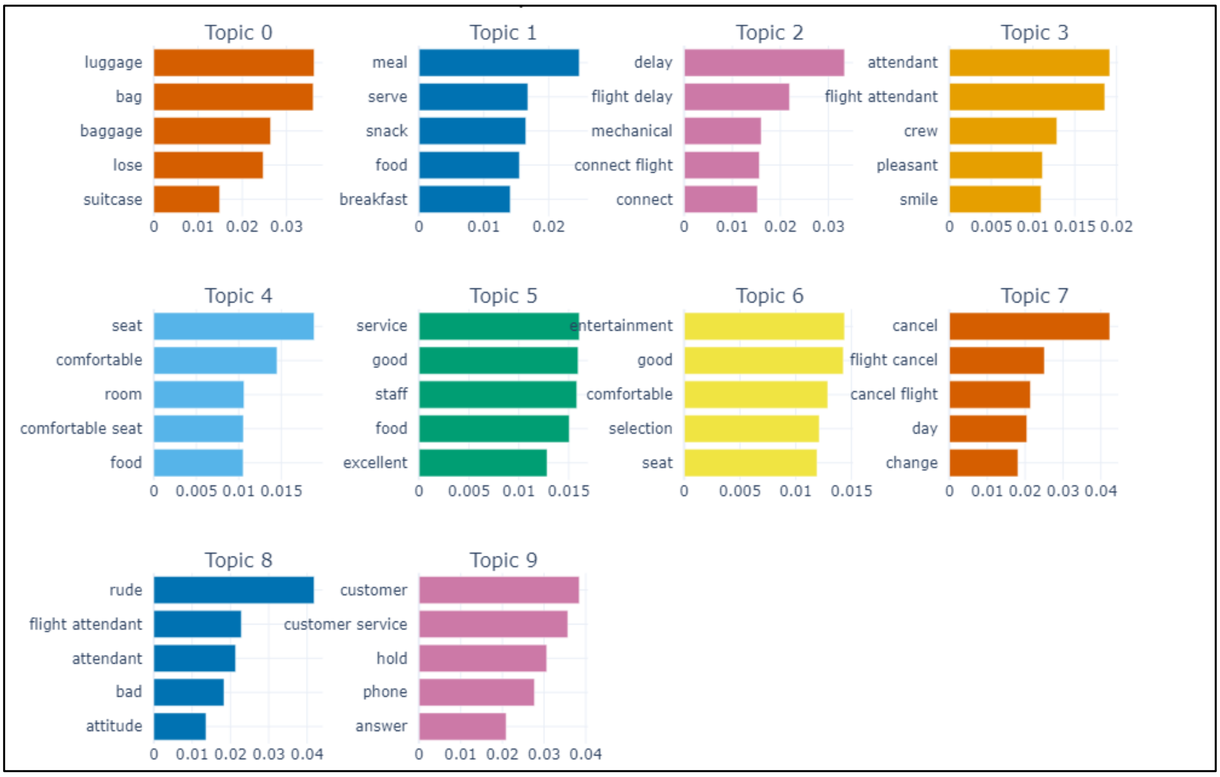
Figure 3. Intertopic Distance Map



Terms representing the top 10 topics with the highest topic word scores are shown in Figure 4.

Figure 4. Top 10 Topics with the Highest Topic Word Scores



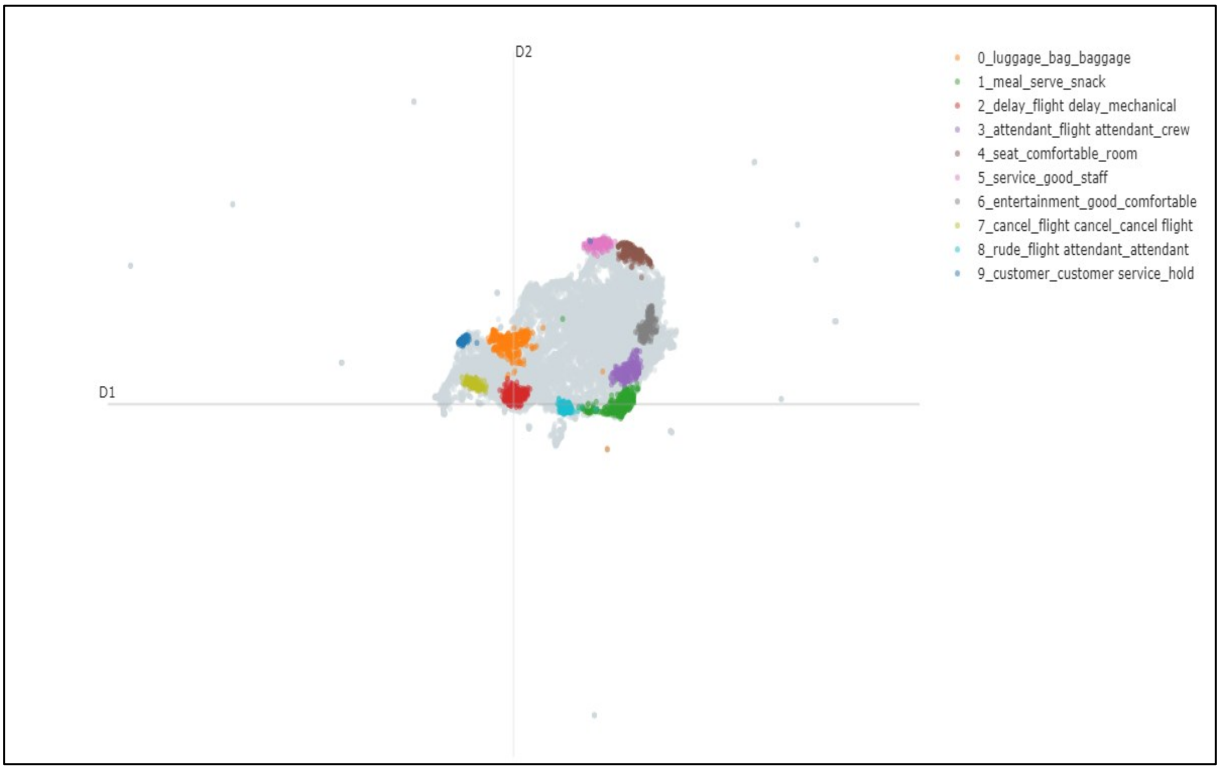
The topics have been named as customer satisfaction dimensions listed in Table 5, based on the expressions representing each topic.

Table 5. Customer Satisfaction Dimensions in FSCs

Topic ID	Topic Number	Dimension
0	1	Luggage
1	2	Food & Drink
2	3	Flight Delays
3	4	Cabin Crew (Positive)
4	5	Seats
5	6	Onboard Service
6	7	Onboard Entertainment
7	8	Flight Cancellations
8	9	Cabin Crew (Negative)
9	10	Customer Service

As seen in Table 5, the prominent customer satisfaction dimensions among passengers traveling with FSC airlines are luggage, food and drink, flight delays, cabin crew (positive), seats, onboard service, onboard entertainment, flight cancellation, cabin crew (negative), and customer service. The distribution of documents according to these topics is presented in Figure 5.

Figure 5. Distribution of Documents According to Topics



Evolution of the identified customer satisfaction dimensions between 2015 and 2022 are presented in Figure 6.

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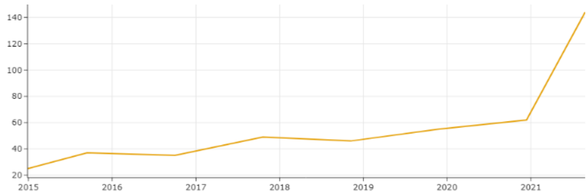
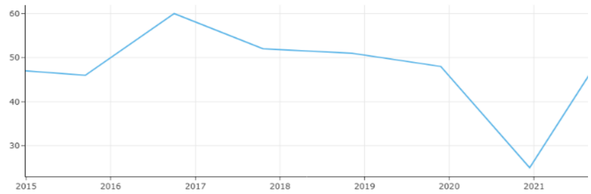
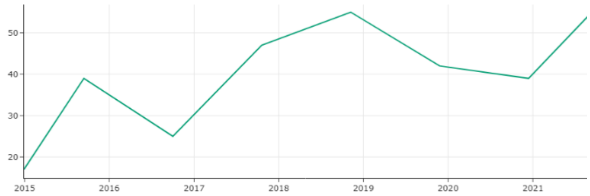
Figure 6. Evolution of the Customer Satisfaction Dimensions



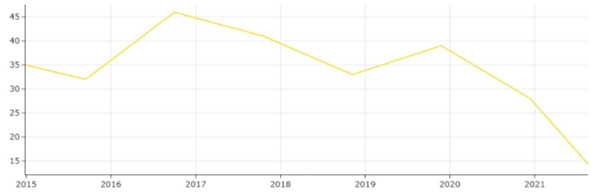
D1: Luggage



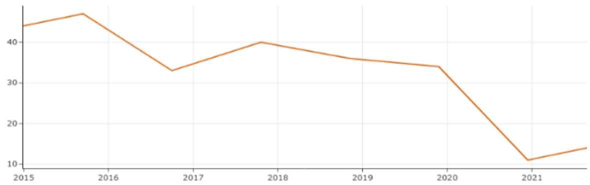
D2: Food & Drink



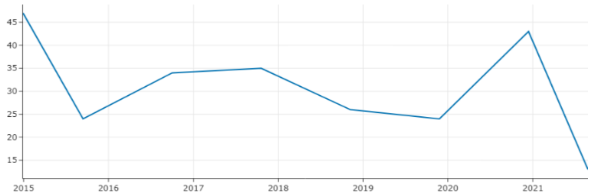
D3: Flight Delays



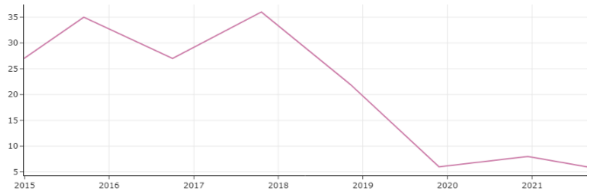
D4: Cabin Crew (Positive)



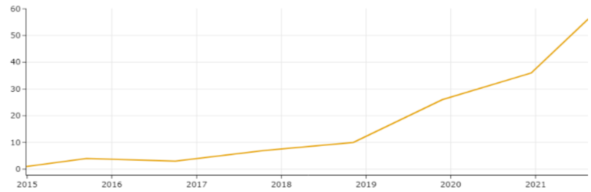
D5: Seats



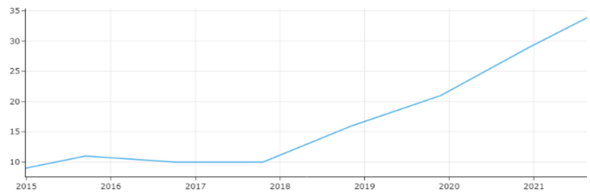
D6: Onboard Service



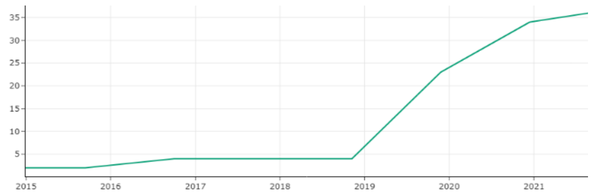
D7: Onboard Entertainment



D8: Flight Cancellations



D9: Cabin Crew (Negative)



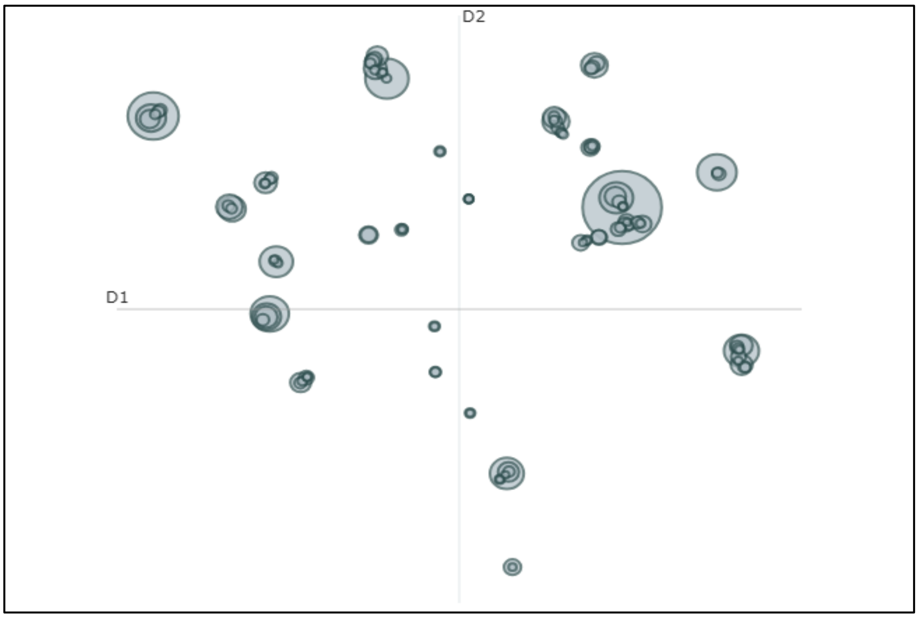
D10: Customer Service

It is observed that customer reviews related to the dimensions of luggage, flight delays, flight cancellations, cabin crew (negative), and customer service have increased over the years, while reviews regarding cabin crew (positive), seats, and onboard entertainment have decreased.

4.2. Dimensions of Customer Satisfaction in LCCs

In order to identify the customer satisfaction dimensions related to passengers traveling with LCC airlines, a topic modeling application was conducted, and 115 topics were obtained. The similarities between the topics and the distances between them are presented in the intertopic distance map shown in Figure 7.

Figure 7. Intertopic Distance Map



Terms representing the top 10 topics, and their corresponding scores are presented in Figure 8.

Figure 8. Top 10 Topics with the Highest Topic Word Scores

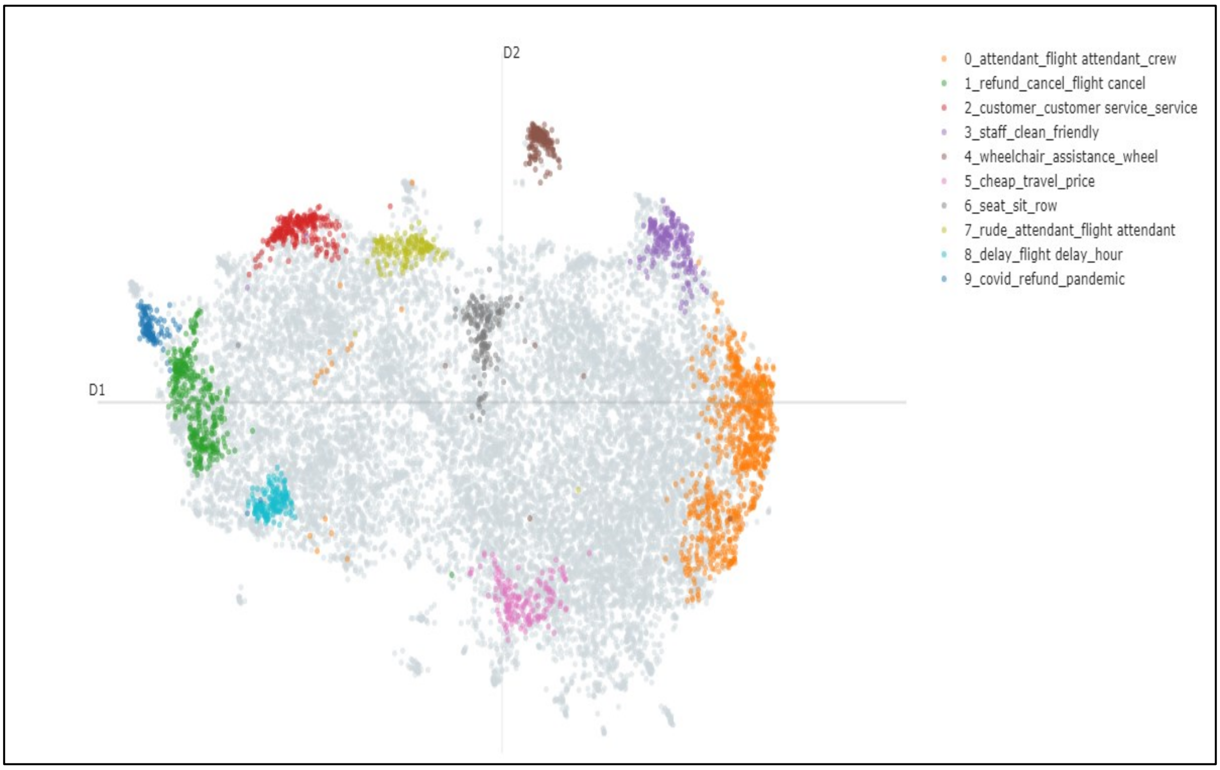
The topics have been labelled as customer satisfaction dimensions, based on the terms of each topic, as shown in Table 6.

Table 6. Customer Satisfaction Dimensions in LCCs

Topic ID	Topic Number	Dimension
0	1	Cabin Crew (Positive)
1	2	Flight Cancellations
2	3	Customer Service
3	4	Onboard Service
4	5	Wheelchair and Assistance Services
5	6	Price
6	7	Seats
7	8	Cabin Crew (Negative)
8	9	Flight Delays
9	10	Covid-19 Related Issues

As seen in Table 6, the prominent customer satisfaction dimensions among passengers traveling with LCC airlines are cabin crew (positive), flight cancellation, customer service, onboard service, wheelchair and assistance services, price, seats, cabin crew (negative), flight delays, and COVID-19 related issues. The distribution of documents according to these topics is presented in Figure 9.

Figure 9. Distribution of Documents According to Topics



Evolution of the customer satisfaction dimensions between 2015 and 2022 are presented in Figure 10.

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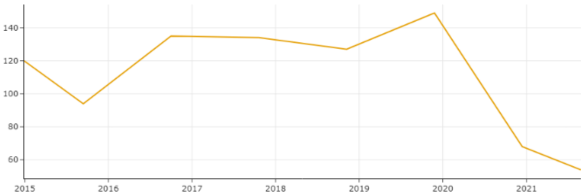
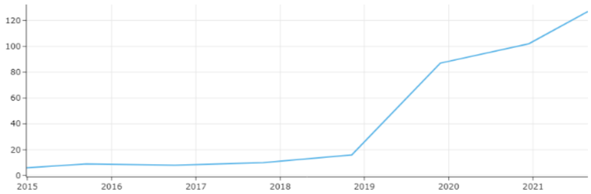
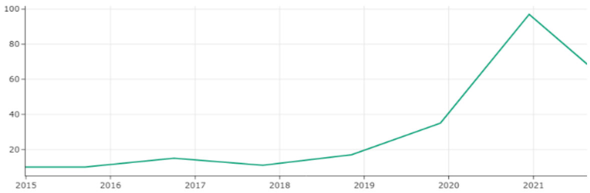
Figure 10: Evolution of the Customer Satisfaction Dimensions



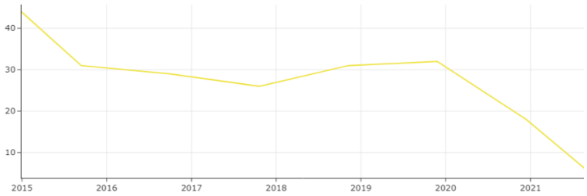
D1: Cabin Crew (Positive)



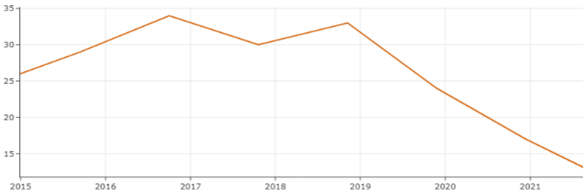
D2: Flight Cancellations



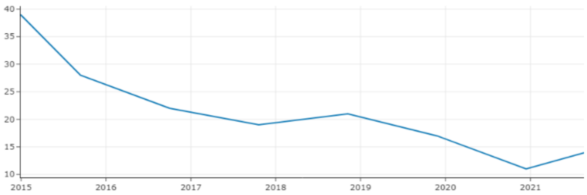
D3: Customer Service



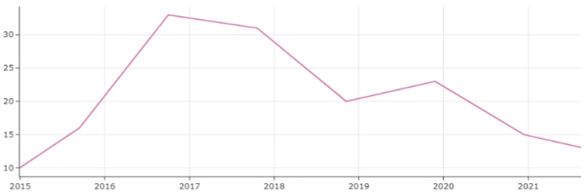
D4: Onboard Service



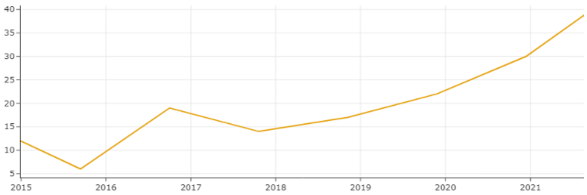
D5: Wheelchair and Assistance Services



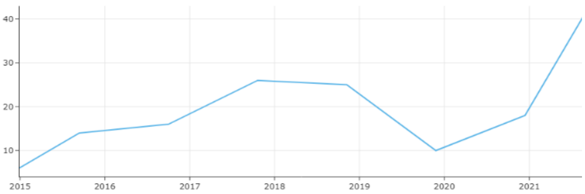
D6: Price



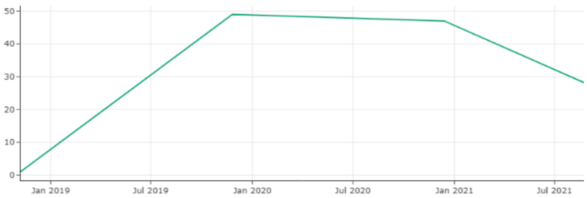
D7: Seats



D8: Cabin Crew (Negative)



D9: Flight Delays



D10: Covid-19 Related Issues

5. CONCLUSION AND DISCUSSION

For airlines operating in a highly competitive environment, achieving customer satisfaction and turning passengers into loyal customers is seen as a significant competitive advantage (Chen, 2008). Therefore, understanding how passengers evaluate airline services and identifying the dimensions that constitute customer satisfaction is of utmost importance (Park et al., 2004). With the advent of new analysis methods brought about by technological advancements, it has become possible to analyze passengers' online evaluations of their travel experiences. Due to the advantages it offers, the use of text mining methods, in addition to traditional methods, has become increasingly common in studies focusing on service quality and customer satisfaction in the airline industry (Korfiatis et al., 2019; Lucini et al., 2020; Sezgen et al., 2019). In this context, the research aims to uncover the dimensions of customer satisfaction from passengers' online review data using contemporary text mining methods. The findings of this study are expected to contribute both to academic literature and to guide airline companies in developing strategies to enhance customer satisfaction.

In the scope of the research, to explore the dimensions of customer satisfaction in airlines, a cross-sectional collection of 32,000 online passenger reviews from various airlines was initially conducted. The airlines selected for this study were those with the highest revenue passenger-kilometers on a global scale. In line with the research questions, the airlines were classified based on their business models, and analyses were carried out to determine the dimensions of customer satisfaction for passengers traveling with both FSC and LCC airlines. The BERTopic model, a topic modeling method that allows for the extraction of contextual information using document-level representations, was chosen for the analyses. The topics derived from the analyses were labeled through human evaluation, resulting in the identification of customer satisfaction dimensions.

For passengers traveling with full-service carriers, the prominent customer satisfaction dimensions were identified as luggage, food and drink, flight delays, cabin crew (positive), seats, onboard service, onboard entertainment, flight cancellation, cabin crew (negative), and customer service. These identified dimensions largely align with previous studies in the field, indicating the consistency of the findings (Atalik, 2007; Forgas et al., 2010; Kos Koklic et al., 2017; Lucini et al., 2020; Stamolampros et al., 2019). It is also notable that in past research, similar dimensions have been labeled differently, such as "helpfulness of cabin crew," or specific service components like "Wi-Fi connectivity" have been categorized under inflight services. However, dimensions such as "type of travel" and "frequent flyer program," highlighted in other studies, are not among the prominent customer satisfaction dimensions in this research. Furthermore, while dimensions related to flight delays and cancellations were identified, no direct dimension related to flight scheduling, as found in the results of Pakdil and Aydın (2007) and Tsafarakis et al. (2018), emerged in this study. Additionally, many similar findings in the literature have been examined within the framework of the SERVQUAL model, which categorizes dimensions such as physical features and responsiveness (Gilbert & Wong, 2003; Hussain et al., 2015; Pakdil & Aydın, 2007; Shiwakoti et al., 2022).

In the next stage, the changes in customer satisfaction dimensions over the years for full-service carriers were examined. The increase in the number of reviews related to luggage is thought to be associated with baggage procedures. Therefore, it is believed that focusing on baggage practices could positively contribute to customer satisfaction. Factors related to in-flight services, such as food and drink and onboard entertainment, continue to maintain their significance in terms of customer satisfaction. However, it is noticeable that the topics emphasized in customer reviews shifted, particularly during and after the COVID-19 pandemic. The rise in the number of reviews concerning flight cancellations and customer service since 2019 is likely linked to disruptions caused by the pandemic. Nevertheless, as highlighted in previous studies, delays and cancellations in flights, even outside of crises, directly impact customer satisfaction. Regarding reviews about cabin crew, it has been observed that negative factors have become more prominent over the years. From this perspective, it is predicted that full-service airlines could positively influence customer satisfaction by developing strategies focused on service variables related to cabin crew.

The identified customer satisfaction dimensions for passengers traveling with low-cost carriers (LCCs) are, in order: cabin crew (positive), flight cancellation, customer service, onboard service, wheelchair and assistance services, price, seats, cabin crew (negative), flight delays, and COVID-19 related issues. The findings largely support previous research by Bakır et al. (2019), Forgas et al. (2010), Kim and Lee (2011), and Sezgen et al. (2019). However, dimensions such as cleanliness, food and drinks, and airport procedures, which were identified in past studies, are not present in these findings. It appears that the onboard service dimension covers factors such as cleanliness. Additionally, wheelchair and assistance services and COVID-19 related issues are unique dimensions identified in this study, distinguishing it from previous research. The wheelchair and assistance services dimension highlights the importance of auxiliary services in airport processes for customer satisfaction. The COVID-19 related issues dimension encompasses topics such as flight cancellations and refunds during the pandemic. Notably, along with price, flight delays and cancellations, as well as service delivery, emerge as prominent factors for passengers traveling with LCCs. An analysis of the changes in customer satisfaction dimensions over time shows an increase in negative reviews related to the cabin crew. Based on the findings, it is suggested that LCCs, like full-service carriers, should focus on improving the service delivery of their cabin crew. Furthermore, the effects of the COVID-19 pandemic are evident in the changes observed over the years in LCC reviews, similar to those for full-service airlines. The pandemic is believed to be the cause of the rise in reviews related to flight cancellations, delays, and customer services. Additionally, the COVID-19 related issues dimension emerged from 2019 onwards, leading to a decline in reviews of other dimensions. Finally, reviews related to the price dimension, which had been emphasized in past research, have gradually decreased over time. This shift suggests that price sensitivity among LCC passengers has diminished, and the factors they prioritize have changed. This change is thought to be a result of LCCs expanding into new markets and reaching new passenger profiles through longer-haul flights, thereby increasing their market share (Tam et al., 2022).

The findings obtained in this research can generally be considered consistent with the literature. When reviewing previous studies, several factors are believed to account for the observed differences. One of these factors is the research model and methodology. Many studies, such as those employing the SERVQUAL model, assess service quality related to customer satisfaction within predefined dimensions, leading to findings being classified within this framework. Similarly, the data collection method and data source are also thought to be significant reasons for variations in findings. The use of data collection tools focused on service quality and customer satisfaction, versus methods like text mining that analyze unstructured data, can result in different outcomes. Limitations related to the geographical region or the specific airline in the sample can also lead to differing results across studies. Beyond these factors, the evolving nature of the airline industry and changing customer expectations over time are considered important reasons why studies conducted at different times may yield different results.

This research provides various theoretical and managerial contributions to the literature on airline customer satisfaction and the airline industry. In the literature, customer satisfaction dimensions have been frequently addressed in the context of service attributes using different research methods. The use of text mining methods in this research to analyze customer reviews introduces an innovative approach that goes beyond traditional surveys and focus group studies, supporting the applicability and validity of text mining techniques in the literature. Additionally, the findings of the research are considered to provide valuable guidance for airline companies in developing strategies to enhance customer satisfaction. The identified customer satisfaction dimensions highlight the areas on which airlines should focus on improving service quality and increasing customer loyalty. Considering these findings, airlines can gain a competitive advantage and enhance customer satisfaction levels by improving their service quality. Moreover, the examination of changes in customer satisfaction over time is expected to contribute to the long-term strategic planning of airline companies.

In addition to the theoretical and managerial contributions presented, this research has certain limitations. The data analyzed in this study are limited to the English language. Analyzing passenger reviews in different languages could provide new insights. Moreover, using multilingual pre-trained models could enable simultaneous analysis of passenger reviews in various languages, which could further expand the scope of research on customer satisfaction. Similarly, employing different data sources to assess customer satisfaction and service quality more comprehensively could lead to the discovery of different findings. Data obtained from sources such as Skytrax, Twitter, other social media platforms, customer complaint websites, and airline customer feedback databases could provide researchers with a broader perspective. Although these platforms have been used in various studies in the literature, it is recommended that the method presented in this study be applied to different data sources in future research. Furthermore, the method used in this study allows for the exploration of topics beyond service quality and customer satisfaction in airlines, which could be an area of focus for future research. Customer satisfaction in airlines can vary not only based on the airline business model but also due to geographic, cultural, demographic factors, or the cabin class in which passengers travel. For example, studies using this method in different regions and cultures could assess how well airline services align with local needs and expectations. Similarly, repeating similar analyses with a focus on passenger profiles not covered in this study—such as those traveling for business or leisure, or those traveling with family versus individually—could help explore variations in satisfaction based on passenger profiles. It is anticipated that such studies would assist airlines in more precisely identifying customer needs and customizing their services according to different customer segments.

In conclusion, this study not only advances the academic discourse on airline customer satisfaction but also provides practical guidance for airlines to enhance their service quality. By addressing the identified dimensions of satisfaction and leveraging the insights derived from text mining, airlines can improve their competitive edge, foster customer loyalty, and ensure sustained success in a dynamic industry landscape. Future studies building on this framework are expected to further refine the understanding of customer satisfaction and its implications, ultimately benefiting both the academic community and the airline industry at large.

DECLARATION OF THE AUTHORS

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