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How Has COVID-19 Affected Airline Passenger Satisfaction? Evaluating The Passenger Satisfaction of European Short-Haul Low-Cost Carriers Pre- and Post-COVID-19

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COVID-19 Havayolu Yolcu Memnuniyetini Nasıl Etkiledi? COVID-19 Öncesi ve Sonrası Avrupalı Kısa Mesafeli Düşük Maliyetli Havayollarında Yolcu Memnuniyetinin Değerlendirilmesi

Öz

Bu çalışma, COVID-19 öncesi ve sonrasında Avrupa'daki en büyük üç kısa mesafeli düşük maliyetli havayolu şirketinin yolcu memnuniyetini etkileyen değişkenlerinde değişim olup olmadığını araştırmayı amaçlamaktadır. Yolcu memnuniyetine ilişkin veri kaynağı olarak Skytrax platformunda yer alan kullanıcı türevli içerikler kullanılmış ve bu ikincil veriler Web Scraper aracı kullanılarak elde edilmiştir. Yolcu memnuniyetine ilişkin sınıflandırma modeli için ikili lojistik regresyon ve modelin sınıflandırma performansını değerlendirmek için ROC analizi kullanılmıştır. Bulgular, koltuk konforu, kabin personeli hizmetleri ve yer hizmetleri hizmet özelliklerinin fiyat-değer algısının önemli belirleyicileri olduğunu ve fiyat-değer algısının iki dönemde de genel memnuniyetin önemli bir belirleyicisi olduğunu göstermiştir. Ayrıca, fiyat-değer algısının en önemli belirleyicisinin yer hizmetleri olduğu ortaya konmuştur. Sonuçlar ayrıca, COVID-19 sonrası dönemde koltuk konforunun tahmin gücünün azaldığını ve yer hizmetlerinin tahmin gücünün arttığını ortaya koymaktadır.

Anahtar Kelimeler: Yolcu Memnuniyeti, Düşük Maliyetli Taşıyıcılar, İkili Lojistik Regresyon

Makale Türü: Araştırma Makalesi

How Has COVID-19 Affected Airline Passenger Satisfaction? Evaluating The Passenger Satisfaction of European Short-Haul Low-Cost Carriers Pre- and Post-COVID-19

Abstract

This paper investigates whether there has been a change in passenger satisfaction drivers for the three largest short-haul low-cost carriers in Europe before and after COVID-19. User-generated content on the Skytrax platform was used as the data source for passenger satisfaction, and these secondary data were scraped using the Web Scraper tool. Binary logistic regression was used for the classification model related to passenger satisfaction, and ROC analysis was used to evaluate the classification performance of the model. The findings suggested that the service attributes of seat comfort, cabin staff services, and ground services are significant predictors of value for money, and the value for money is a significant determinant of overall satisfaction in both periods. Additionally, it was revealed that ground service is the most important determinant of the value for money perception. The results also indicate that in the post-COVID-19 period, the predictive power of seat comfort has decreased while the predictive power of ground services has increased.

Keywords: Passenger Satisfaction, Low-Cost Carriers, Binary Logistic Regression

Paper Type: Research Article

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1. Introduction

The air transportation served 4.5 billion passengers in 48.044 routes and 46.8 million flights and contributed 3.5 trillion US $ to the global GDP in 2019 (ATAG, 2020). Even if the passenger number fell to 1.8 million due to COVID-19 (IATA, 2021), the industry has been growing, excluding some catastrophic events, such as the Gulf War, the Oil crises, COVID-19, and so on. It is anticipated that the industry will transport 8,2 billion people and contribute 6,3 trillion US $ to the world GDP if things go well. On the other hand, in case of low growth, these values would be 7.4 billion passengers and 6 trillion US $ (ATAG, 2020). In 2050, ten billion passengers are expected to be served (IATA, 2022). So, increasing demand must be met efficiently. Therefore, airlines, the fundamental component of the aviation industry (Martini, 2022), have a vital role.

All the systems are subject to the environment to sustain its life (Luhmann, 2002/2013). In addition, the fit factors of an organization's lifespan are the environment and competition (Hannan & Freeman, 1977). With deregulation in air transport industry in 1978, ticket prices have started to fall, and airlines, which are open systems, began to operate in more competitive markets (Goetz, 2002). Competitiveness made presenting high-quality services necessary (Ostrowski et al., 1993). Therefore, more high-quality service means longevity for airlines (Park et al., 2004). Due to both competitiveness and raising awareness of the service quality of travelers (Chou et al., 2011), exquisite passenger satisfaction is one of the foremost assets for airlines (Namukasa, 2013). Therefore, airlines must understand the passengers' expectations of their services to meet demanding desires and needs for obtaining high satisfaction (Suki, 2014).

As a global crisis that came out of the blue, COVID-19 changed people's lifestyles, habits, and behaviors (León-Zarceño et al., 2021; Hagger & Hamilton, 2022). Consequently, it inherently influenced the customers' expectations and perceptions concerning the services offered to them (Yalcin Kavus et al., 2022). This made it more challenging to understand and satisfy people who were already very volatile. For example, the study concentrating on Seville Airport (Lopez-Valpuesta & Casas-Albala, 2023) showed that the second COVID-19 year (i.e., 2021) was worse than the first COVID-19 year (i.e., 2020) in terms of customer satisfaction. When it comes to airlines, the paper focusing on the top 100 airlines based on the World Airline Awards (Wang et al., 2023) revealed that staff service and value for money have no impact on the recommendation intent of passengers, and inflight entertainment has a negative effect. Pereira et al. (2023), investigating the passenger satisfaction of sixteen European air carriers, found that staff behavior is the primary factor affecting passengers' satisfaction after the pandemic. In previous research, the dataset included both full-service network carriers and low-cost carriers. However, when considering passenger satisfaction, differences between the two main business models in the airline industry, full-service network carriers (FSNCs) and low-cost carriers (LCCs), should be taken into account (Lohmann & Koo, 2013; Pereira et al., 2023; Sezgen et al., 2019). Because the fundamental business strategies and services provided by these two business models lead to significant differences in key features of airline service quality (Lim & Lee, 2020). Low-cost carriers typically offer no-frills services with a focus on cost efficiency, while full-service network carriers provide a broader range of amenities and services at higher prices. Therefore, to enhance the resolution of the analysis of passenger satisfaction between before and after COVID-19, the focus has been particularly on the low-cost carrier business model, and even more so on carriers that excel in short-haul operations within low-cost carrier business model. A comprehensive literature review revealed a gap in prior studies concerning the changes in passenger satisfaction among European short-haul low-cost carriers before and after COVID-19, motivating this study to address this gap. This paper is structured as follows. Section 2 summarizes the user-generated content and big data concepts and delivers the hypotheses proposed. Section 3 comprises the data collection and methodology. Section 4 succinctly presents the findings. Section 5 discusses the results, states the limitations, offers suggestions for future studies, and highlights the potential implications of the study for both the literature and airline companies.

2. Literature Review

2.1. User Generated Contents (UGCs)

As digitalization has accelerated, concepts such as Web 2.0, smartphones, open sources, the Internet of Things (IoT), artificial intelligence, and machine learning have been implemented, resulting in a gigantic growth in user-generated contents (UGCs) on the Internet. User-generated content (such as posts on social media and bulletins, ratings, forums, online product reviews, and so on) has provided new techniques to create unique measurements of customer behavior and comprehend various research problems in numerous domains related to strategic management in marketing, such as customer relationship management and market segmentation. There are countless online platforms, such as Yelp!, Flicker, Amazon, Google, Facebook, TripAdvisor, and Skytrax, allowing users to share their experiences and opinions (Lu & Stepchenkova, 2014; Xiang, 2017; Mastrogiacomo et al., 2021; Rasool & Pathania, 2021).

UGCs mean printed or visual media content that regular people create and share on the web platforms (Daugherty et al., 2008). UGCs function as electronic word-of-mouth marketing by allowing consumers of a product or service to publicly share their experiences, giving potential customers an insight into the products/services (Trusov et al., 2009). Accordingly, people seeking to reduce the risks pursue comments about relevant goods/services (Smith et al., 2004). More specifically, UGCs enable companies delivering high-quality services to benefit from cost-free marketing through satisfied customers, while those providing inadequate services can identify their shortcomings.

There are various fields UGCs have been studied, such as tourism and hospitality (Cox et al., 2009; Mariné-Roig & Clavé, 2015; Ukpabi & Karjaluoto, 2018; Wang et al., 2020; Li et al., 2023), hotel industry (Williams et al., 2010; Ye et al., 2011; Barreda & Bilgihan, 2013; Herrero Crespo et al., 2015; Jang & Moutinho, 2019), online food ordering (Geissinger et al., 2020; Ray & Bala, 2020; Batouei et al., 2023; Khan et al., 2023; Saydam et al., 2023), airport service quality (Bogicevic et al., 2013; Martin-Domingo et al., 2019; Molaei & Hunter, 2019; Barakat et al., 2021; Araslı et al., 2023), airline service quality (Siering et al., 2018; Lucini et al., 2020; Chatterjee et al., 2021; Rasool & Pathania, 2022; Chatterjee et al., 2023). Due to the enormously increasing volume of UGC data sources and the fact that UGCs are voluntarily created by users, providing valuable insights into customer behavior, UGCs from airline passengers were used as the data source for this study.

2.2. Big Data and Web Scraping

Big data, an emerging significant research domain in various fields like decision-making and information sciences, is particularly attractive in numerous areas, such as data mining, machine learning, social networks, and more (Mohamed et al., 2019). Big data is a term used to describe a collection of information assets demanding distinct analytical processes due to their high volume, variety, and velocity for extracting valuable insights (De Mauro et al., 2016). In this context, online platforms delivering a myriad of UGCs have big data waiting to be transformed into meaningful information. Dealing with unstructured data that rapidly growing UGCs can be a challenging task (Grover & Kar, 2017). Additionally, since online UGC databases have diverse access structures data can be acquired through Application Programming Interface (API), where available, or by employing alternative methods such as web scraping (Blazquez & Domenech, 2018).

Web scraping, a characteristic method of extracting unstructured data from an online platform and converting it into structured data, enables countless data to be acquired effortlessly soon (Dogucu

& Çetinkaya-Rundel, 2020). The method has admirable benefits, such as allowing to obtain daily updated data smoothly and does not need API (Skoulikaris & Krestenitis, 2020). Web scraping can be utilized for both exploratory and confirmatory examinations, and it is legal and ethically sound, as long as copyrighted data is not used for commercial purposes (Han & Anderson, 2020). On the other hand, technological development made the scraping process so accessible that one can utilize this method effortlessly, including through browser extensions. Numerous papers in the literature have employed these extensions (Li et al., 2020; Dağhan & Gündüz, 2022; Cuéllar et al., 2023).

2.3. Hypotheses

The empirical study by Kim and Lee (2011) indicated that responsiveness and tangibles are the most significant dimensions of customer satisfaction for LCCs. Additionally, Saha and Theingi (2009) conducted a survey and obtained 1212 responses based on LCC passengers and expressed that cabin staff service influences the passengers' feedback. Satisfied customers deliver positive WOM communication and have elevated repurchase intentions. Given that value for money significantly predicts word-of-mouth communication and satisfaction (Rajaguru & Hassanli, 2018; Souki et al., 2023), and considering the influence of cabin staff service on value for money, this study hypothesizes the following:

H1: Cabin staff service is a significant predictor of value for money.

Fourie and Lubbe (2006) investigated the drivers of airline company selection in the context of the airline business model. The authors suggest that seat comfort is the most significant service attribute affecting airline selection regardless of the business model. Brochado et al. (2019) investigated the primary themes associated with the high value of money. The results revealed that passengers having a high perceived value for money consistently share reviews regarding seat comfort. Accordingly, based on the literature, the following hypothesis is proposed:

H2: Seat comfort is a significant driver of value for money.

Ground service is accepted as a critical factor for customer satisfaction (Park et al., 2020). Air carriers can generate positive WOM by enhancing the quality of ground services (Sulu et al., 2022). Delivering high-quality ground services yields recommendation and satisfaction (Ban & Kim, 2019) as it affects customer perception positively (Siering et al., 2018). Therefore, this evaluation delivers the following hypothesis:

H3: Ground service is a significant explainer of value for money.

Although there are various definitions of service quality, in its simplest form, it is the degree to which customers' anticipations are met (Kağnıcıoğlu & Özdemir, 2016). Therefore, services have a heterogeneous structure by perceived quality. Airlines should, therefore, offer a service that makes customers feel they are getting value for money. Value for money is not simply the lowest decision since the concept has benchmarking to other options (Barton et al., 2019). Hence, it can be said that value for money is the response to the question: "Was it worth it?". Value for money is a vital consideration regardless of the airline business model and is indispensable for LCCs to acquire customer satisfaction (Forgas et al., 2010; Rajaguru, 2016). In this sense, this paper proposes the hypothesis as follows:

H4: Value for money is a significant determinant of customer satisfaction.

On the other hand, some service attributes, such as free-of-charge food and beverages, inflight entertainment with a large assortment of movies and video games for relaxation and enjoyment, and cabin Wi-Fi with stable connection and acceptable speed, are substantially associated with full-service carriers (Byun & Lee, 2016; Bogicevic et al., 2017; Lee et al., 2018; Shen & Yahya, 2021). In this context, no hypotheses are proposed concerning the service attributes mentioned above. To summarize all hypotheses proposed, the research model is illustrated in Figure 1.

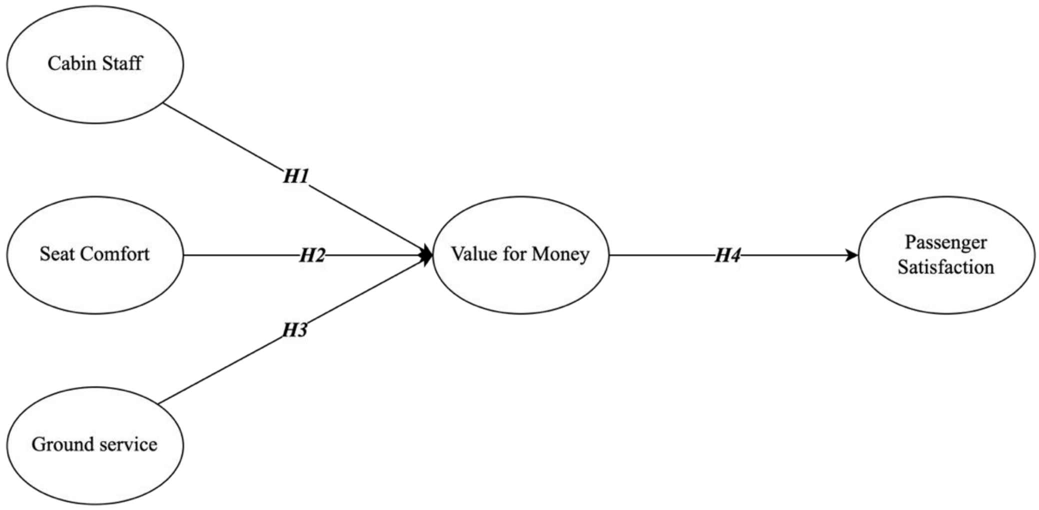


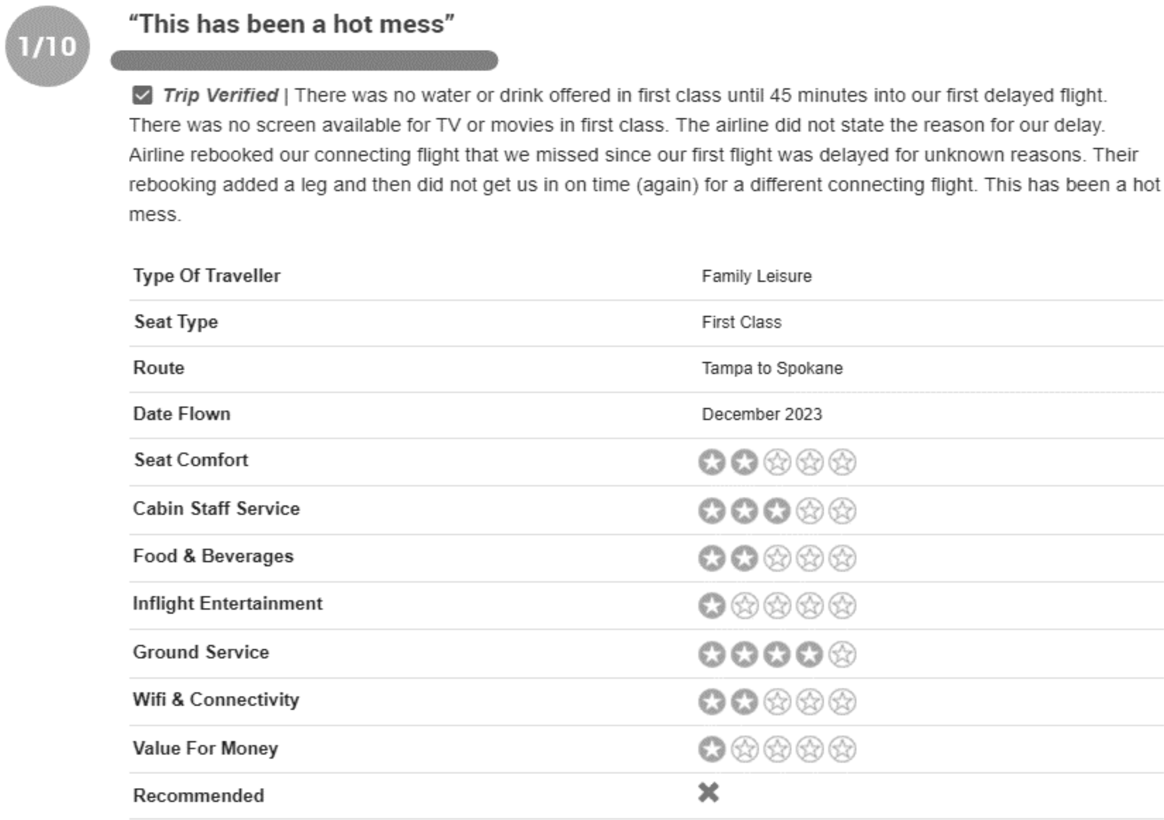
Figure 1. Research model

Accordingly, two consecutive logistic regression models were developed for each pre- and post-COVID-19 period considering the research model above. For both the pre- and post-COVID-19 periods, the first set of models evaluates the effects of cabin staff, seat comfort, and ground services on value for money. Similarly, for both periods, the second set of models predicts the impact of value for money on overall satisfaction. Further explanations on logistic regression models are provided in the following section.

3. Research Design and Methodology

3.1. Research Design

The study uses secondary data from Skytrax (https://www.airlinequality.com). Skytrax is highly utilized in service quality literature (Han et al., 2012; Atalık et al., 2019; Punel et al., 2019; Song et al., 2020; Bae & Chi, 2021; Bunchongchit & Wattanacharoensil, 2021; Halpern & Mwesiumo, 2021; Bakır et al., 2022; Brochado et al., 2022; Kılıç & Çadırcı, 2022; Araslı et al., 2023). It is an online forum consistently utilized by customers who want to share their flight experiences. The forum has different review segments, including airline reviews, airline seats, airline lounges, and airport reviews. Figure 2 indicates an airline review example in Skytrax. Airline reviews start with the review header, customer's name, nationality, review date, overall satisfaction, review text, continue with the type of traveler, seat type, route, date flown, and seven service attributes ranging from one to five (seat comfort, cabin staff service, food & beverages, inflight entertainment, ground service, wifi & connectivity, value for money), and end with recommendation as yes/no.



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"This has been a hot mess"

Trip Verified | There was no water or drink offered in first class until 45 minutes into our first delayed flight. There was no screen available for TV or movies in first class. The airline did not state the reason for our delay. Airline rebooked our connecting flight that we missed since our first flight was delayed for unknown reasons. Their rebooking added a leg and then did not get us in on time (again) for a different connecting flight. This has been a hot mess.

Type Of Traveller	Family Leisure
Seat Type	First Class
Route	Tampa to Spokane
Date Flown	December 2023
Seat Comfort	★★☆☆☆
Cabin Staff Service	★★★☆☆
Food & Beverages	★★☆☆☆
Inflight Entertainment	★☆☆☆☆
Ground Service	★★★★☆
Wifi & Connectivity	★★☆☆☆
Value For Money	★☆☆☆☆
Recommended	✖

Figure 2. Review example

In accordance with the aim of the study, the pre- and post-COVID-19 periods were determined as illustrated in Figure 3.

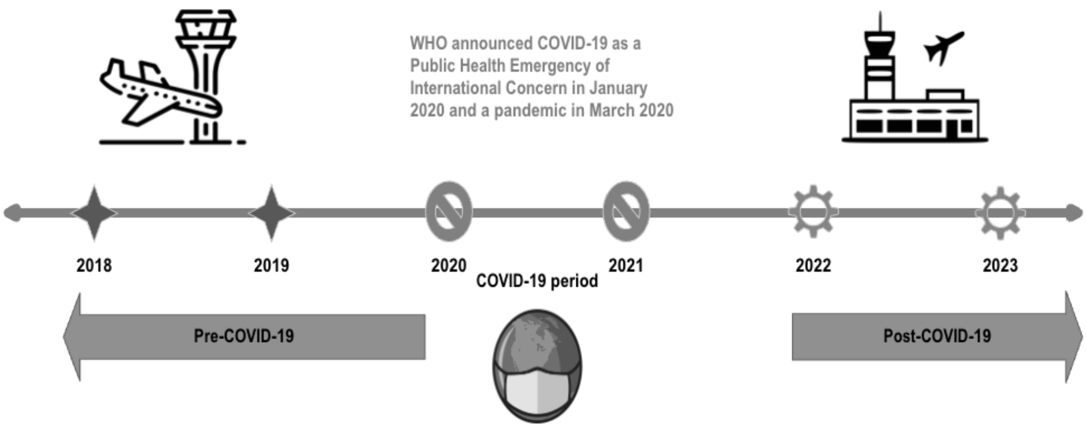

Figure 3. Analysis periods

Following the literature (Lopez-Valpuesta & Casas-Albala, 2023; Popp et al., 2023), the 2022-2023 period is considered as the post-COVID-19 era. In addition, the 2018-2019 period is regarded as the pre-COVID-19 era. The research flow is illustrated in Figure 4.

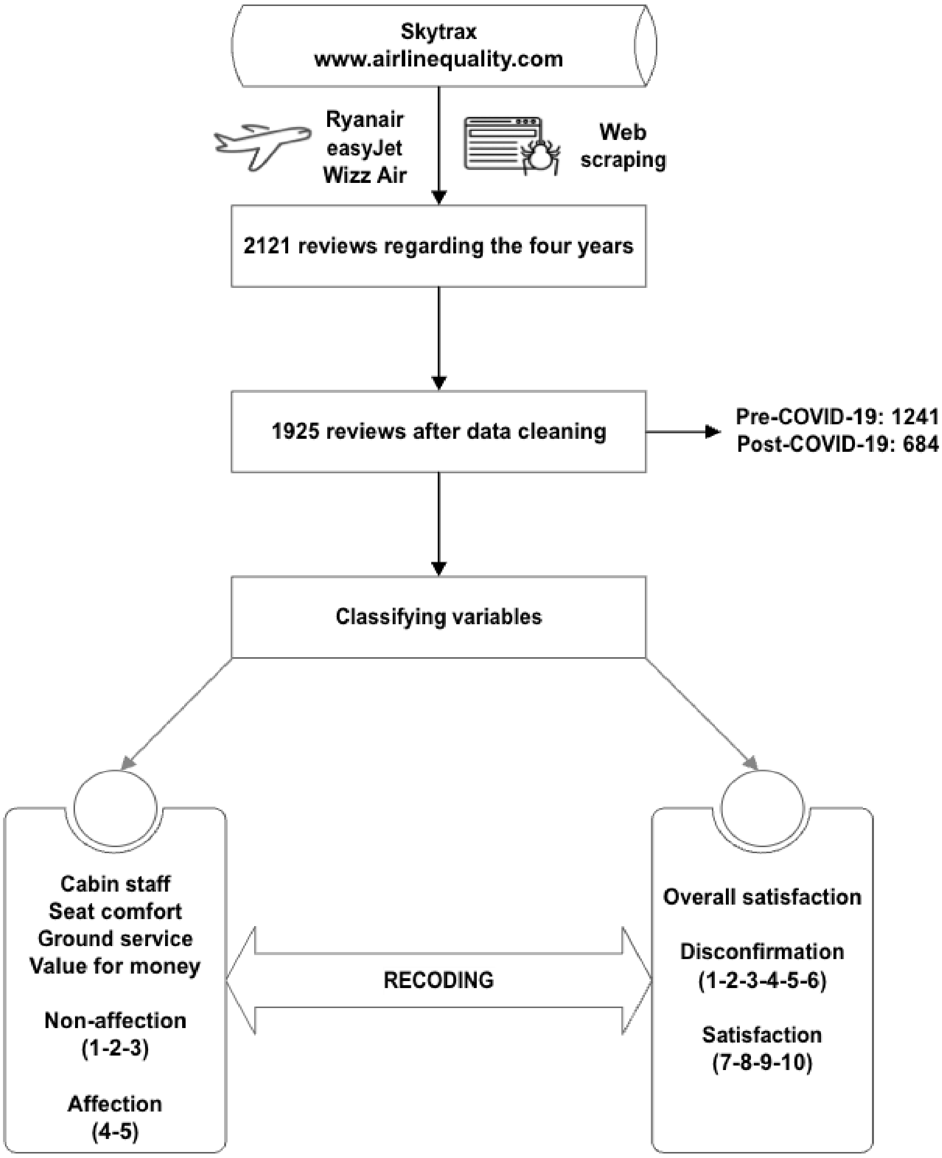

Figure 4. Research flow

Initially, on December 1, 2023, the passenger reviews from Skytrax were extracted for the three leading short-haul low-cost carriers in Europe, covering the periods 2018-2019 (pre-COVID-19) and 2022-2023 (post-COVID-19). Afterward, the missing values from the 2121 reviews scraped were cleaned up in the raw dataset and 1925 reviews were acquired as final dataset. Finally, all variables were categorized into two groups. Following Halpern & Mwesiumo (2021), the star rating values of four main variables (cabin staff, seat comfort, ground service, value for money) were divided into two groups: affection (star ratings of four to five) and non-affection (star ratings of one to three). Affection refers to service attributes that exceed or at least meet customer expectations, while non-affection refers to service attributes that fall short of expectations. In addition, following Dike et al. (2023), the values of overall satisfaction variable were also categorized into two groups: disconfirmation (rating one to six) and satisfaction (seven to ten).

3.2. Methodology

This paper employs the logistic regression analysis (LRA) for several reasons. Linear regression models are not suitable for predicting the categorical outcome (i.e., dependent) variable (Al-Ghamdi, 2002). Even if the linear models are effective prediction tools, they require normal distribution (Casson & Farmer, 2014). On the other hand, the LRA allows one to predict the dichotomous (i.e., binary) or polychotomous explained (i.e., independent) variable (Hosmer et al., 2013). Besides, the LRA does not require normal distribution (Pallant, 2020). Midi et al. (2010) expressed that multicollinearity is not a vital problem for binary LRA since it does not significantly modify the coefficients' estimates but their reliability. Besides, Ohyver et al. (2016) stated that ridge logistic regression should be employed if multicollinearity arises. One can check whether multicollinearity exists with the Variance Inflation Factor (VIF). The VIF value of 10 (or more) is an indicator of multicollinearity (Chan et al., 2022). In addition, the tolerance value should be higher than 0.20 (Menard, 2003). The LRA requires all observations in the dataset to be independent (Alshahrani et al., 2021). Violating this assumption leads to poor fit, also called overdispersion (Allison, 1999).

The linearity assumption of linear models, the linear relationship between dependent and independent variables, is violated as the dependent variable is categorical. Therefore, the LRA uses a transformation dubbed logit to predict dichotomous/polychotomous outcome (Field, 2018). The underlying reason for the logit transformation relies on the basic parameters of the LRA. A binary dependent variable should range between 0 (zero) and 1 (one). In contrast, the outcome variables in the linear model might take on any number. The logit unravels this issue by transforming the equation of linear regression to acquire the natural logarithm of the odds. The odds ratio -also known as Exp (β)- means the occurrence probability of the outcome P(Y) is divided by the non-occurrence probability 1-P(Y) (Stoltzfus, 2011). The transformation is given in Equation (1) (Newgard et al., 2004):

$$\ln(odds) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \quad (1)$$

In Equation (1), β_0 is intercept, $\beta_1, \beta_2 \dots \beta_n$ are coefficients, and X_1, $X_2 \dots X_n$ are regressors. Accordingly, the logistic model with multi-regressors is formulated as Equation (2) (Field et al., 2012):

$$P(Y) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_n X_{ni})}} \quad (2)$$

In Equation (2), e represents the base of natural logarithms, also known as Euler's number. The LRA also differentiates from the linear models in terms of goodness-of-fit tests. Instead of log-likelihood (LL), the deviance statistic is more suitable for the LRA. It is also known as -2LL since it is calculated as -2 x LL (Field et al., 2012). A -2LL value approaching zero means that the model is becoming more fitting (Domínguez-Almendros et al., 2011). Another fit measurement is R^2. Generalized R^2 has the weakness that its upper bound is less than 1 due to the discrete outcome variable (Allison, 1999). Therefore, logistic regression employs pseudo R^2. There are several R^2, such as Mc Fadden R^2, Cox and Snell R^2, and Nagelkerke R^2 (Liu, 2016). Even if Cox and Snell R^2 has a theoretical maximum of 1, it never attains in practice (Field et al., 2012). Therefore, Nagelkerke R^2 fixing this issue is highly utilized. In contrast to the -2LL, the pseudo R^2 value approaching 1 means that the model is becoming more fitting (Field, 2018).

In logistic regression terminology, two important terms related to its performance are sensitivity and specificity. They are the correct classification rates of the first and the second group, respectively (Boateng & Abaye, 2019). In addition, the Receiver Operating Characteristics (ROC) curve analysis, which is a curve of sensitivity and 1 – specificity and is more informative than the classification table, is conducted. A high area under the curve indicates the higher robust prediction of the logistic regression model (Agresti, 2002). The ROC closer to the top left of the coordinate plane indicates fewer false negatives (i.e., higher sensitivity) and fewer false positives (i.e., higher specificity) (Carter et al., 2016). In addition, the AUC (area under the ROC curve) value is a widely utilized discriminative indicator (Dreiseitl & Ohno-Machado, 2002). The AUC value, representing the overall performance of a logit model, varies from 0.5 to 1.0 (Chen & Wu, 2017). The AUC value between 0.6 and 0.7 indicates poor performance, 0.7 and 0.8 acceptable performance, 0.8 and 0.9 means good performance, and higher than 0.9 demonstrates excellent performance (Elkahwagy & Kiriacos, 2024).

4. Results

The LRAs and ROC curve analyses were conducted by Jamovi open statistical software. As an open project, the Jamovi, which was founded by Jonathan Love, Damian Dropmann, and Ravi Selker, is free and community-driven (The jamovi project, 2023). Following the purpose of the paper, 1925 reviews of three short-haul low-cost carriers in Europe were extracted from Skytrax platform. In the pre-COVID-19 period, Ryanair had 583 reviews, while easyJet and Wizz Air shared the same number as 329. On the other hand, the numbers of reviews in the post-COVID-19 era belonging to Ryanair, easyJet, and Wizz Air are 233, 153, and 298, respectively. The VIF and tolerance values for pre-COVID-19 (PrC) and post-COVID-19 (PoC) models are given in Table 1.

Table 1. Multicollinearity checks for pre-COVID-19 and post-COVID-19 models

Period	Predictors	VIF	Tolerance
Pre-COVID-19 (PrC)	Seat comfort	1.05	0.948
	Cabin staff	1.08	0.925
	Ground services	1.03	0.972
Post-COVID-19 (PoC)	Seat comfort	1.07	0.933
	Cabin staff	1.08	0.905
	Ground services	1.03	0.940

Based on Table 1, there is no evidence of multicollinearity since the VIF and tolerance values are not at the threshold of 10 and 0.2, respectively. (Menard, 2003; Field et al., 2012; Chan et al., 2022). Also, the independence assumption was checked using Pearson residual analysis, one of the most employed measurements for residual analysis in logistic regression (Lai et al., 2021). Zhang (2016) expressed that the straighter the trend in Pearson residual plots, the better the fit of the model. In addition, the relationship between the variables and the residual must be statistically insignificant (i.e., $p>.05$). Residual analysis was conducted using the car package in R (Fox & Weisberg, 2019). The Pearson residual findings for the PrC and the PoC models are illustrated in Figure 5. Note that SC represents the seat comfort, CSS stands for cabin staff service, GS denotes ground service, and VFM refers to value for money. In Figure 5, the first two columns on the left pertain to the PrC model, while the last two columns on the right correspond to the PoC model. According to the plots of the PrC model, there is no evidence of a relationship that could jeopardize the independence assumption since the line is mostly straight. In addition, according to the plots of the PoC model, there is a curvature in the line of the seat comfort attribute. However, this does not mean that the model's independence of the residuals is completely violated. Because it is also necessary to check whether the relationship between variables and residuals is statistically significant. Therefore, to assess the independence of the residuals, the relationship between variables and residuals was examined, and the results are given in Table 2. The results revealed that there is no statistically significant relationship between the variables and the residuals in both logistic regression models. Since all p-values are above .05, the assumption of independence of the residuals has not been violated.

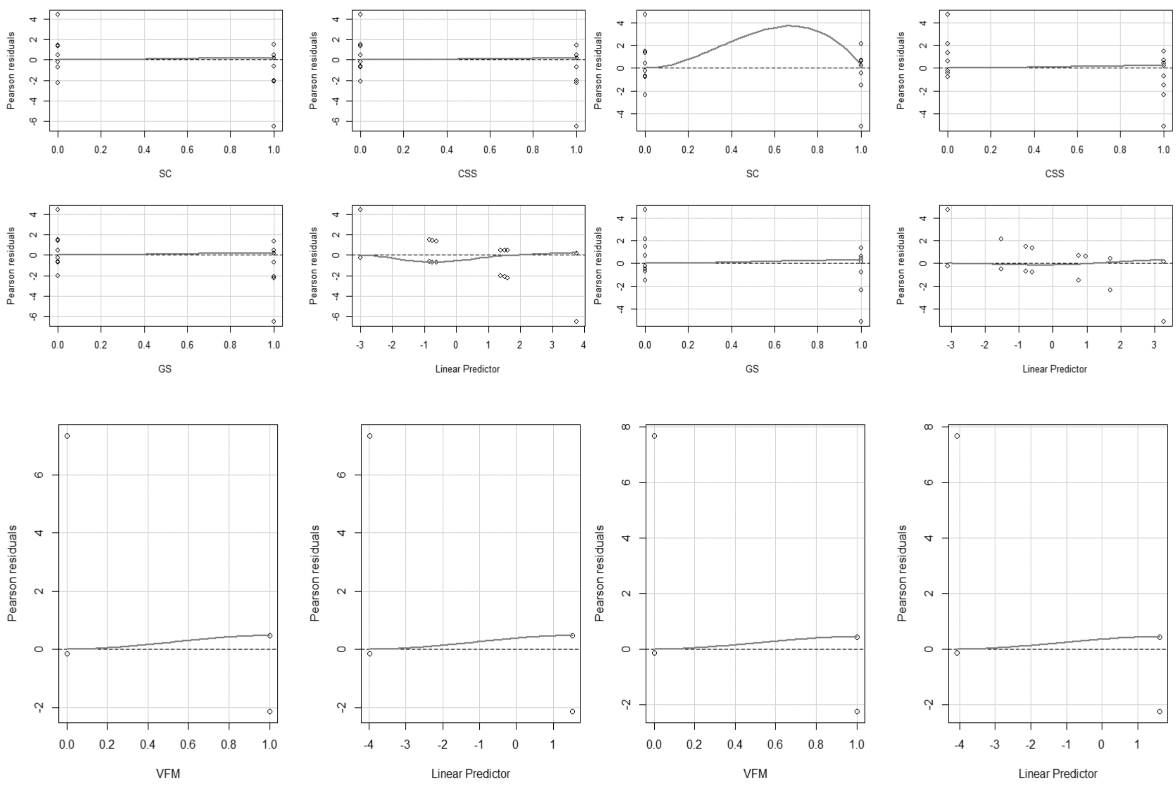

Figure 5. Pearson Residuals Plots

Table 2. Results of the relationship between the variables and residuals

Models	Variables	p-value
PrC	SC	1
	CSS	1
	GS	1
	VFM	1
PoC	SC	1
	CSS	1
	GS	1
	VFM	1

Table 3 conveys the fit measurement of the models belonging to the pre-COVID-19 period.

Table 3. Fit measurements of the pre-COVID-19 models

	Overall Model Test					Omnibus Likelihood Ratio Tests			
Models	**-2LL**	R_N^2	χ^2	**df**	**p**	**Predictors**	χ^2	**df**	**p**
Pre-COVID-19-1 (PrC-1)	639	0.676	756	3	< .001	Seat comfort	57.3	1	< .001
						Cabin staff	96.2	1	< .001
						Ground service	81.5	1	< .001
Pre-COVID-19–2 (PrC-2)	463	0.757	840	1	< .001	Value for money	840	1	< .001

Note: R_N^2 represents the Nagelkerke R^2

Accordingly, both model is statistically significant (PrC-1: $\chi^2(3,1241)$: 756, -2LL: 639, p < .001; PrC-2: $\chi^2(1,1241)$: 840, -2LL: 463, p < .001). According to Nagelkerke R^2, the PrC-1 model explains 67.6% of the variance in value for money in the pre-COVID-19 period. Additionally, value for money explains 75.7% of the variance in overall satisfaction in the same period. Table 4 indicates the classification performance of the pre-COVID-19 models.

Table 4. Classification table of the pre-COVID-19 models

Models	Observed	Predicted		Performance
PrC-1		**Non affection**	**Affection**	**% Correct**
	Non affection	906	25	97.3
	Affection	91	219	70.6
	Overall percentage			90.7
PrC-2				
		Disconfirmation	**Satisfaction**	**% Correct**
	Disconfirmation	914	56	94.2
	Satisfaction	17	254	93.7
	Overall percentage			94.1

Note: The cut-off value is set to 0.5

Accordingly, both pre-COVID-19 logistic regression models have more than 90% success of classification. Table 5 presents the results of binominal LRA regarding the pre-COVID-19 models.

Table 5. Logistic regression results of pre-COVID-19

	Model Outcomes: Value for money in PrC-1, Satisfaction in PrC-2						95% Confidence Interval	
Model	**Predictor**	**Estimate**	**SE**	**Z**	**p**	**Exp (β)**	**Lower**	**Upper**
PrC-1	Intercept	-2.99	0.149	-20.10	< .001	0.050	0.037	0.067
	Seat comfort (X_1): Affection – Non affection	2.14	0.293	7.32	< .001	8.512	4.796	15.107
	Cabin staff (X_2): Affection – Non affection	2.24	0.222	10.08	< .001	9.373	6.065	14.484
	Ground service (X_3): Affection – Non affection	2.36	0.268	8.81	< .001	10.597	6.269	17.913
PrC-2	Intercept	-3.98	0.245	-16.3	< .001	0.018	0.011	0.030
	Value for money (X_4): Affection – Non affection	5.50	0.286	19.2	< .001	243.861	139.266	427.012

Reference level: Non-affection in PrC-1, Disconfirmation in PrC-2

It is clear from Table 5 that the contributions of all predictors on value for money and satisfaction are statistically significant for both models (p < .001). So, the logit equations of the models are proposed in Equations (3) and (4).

$$Logit(value\ for\ money) = -2.99 + 2.14X_1 + 2.24X_2 + 2.36X_3 \quad (3)$$

$$Logit(satisfaction) = -3.98 + 5.50X_4 \quad (4)$$

According to Table 5, all variables have Exp (β) higher than 1. So, the most potent predictor of value for money is ground service, having a 10.597 odds ratio. It means that high perceived quality belonging to ground service increases the likelihood of value for money by 10.597 times (Δodds= + 959%). Similarly, higher perceived quality of cabin staff and seat comfort services increases the likelihood of perceiving higher value for money by 9.373 (Δodds= + 837%) and 8.512 (Δodds= + 751%) times, respectively. In addition, according to the PrC-2 model, high value for money perception increases the likelihood of passengers being satisfied by 243.861 times (Δodds= + 24286%). The ROC curves are illustrated in Figures 6 and 7, and predictive measures of the models are reported in Table 6. The curve is quite close to the upper left, which means the discrimination ability of the model is high. Moreover, the AUC values are higher than 0.9, which points out that the overall performances of the pre-COVID-19 models are excellent.

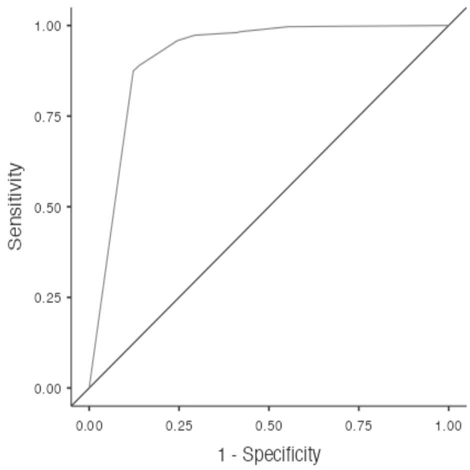

Figure 6. ROC curve for PrC-1 model

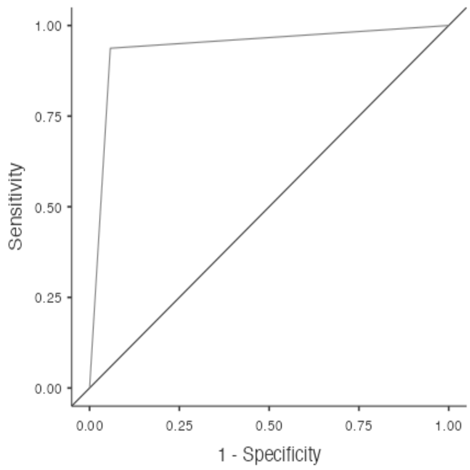

Figure 7. ROC curve for PrC-2 model

Table 6. Predictive measures of the PrC models

Models	Accuracy	Specificity	Sensitivity	AUC
PrC-1	0.907	0.973	0.706	0.914
PrC-2	0.941	0.942	0.937	0.940

Note: The cut-off value is set to 0.5

Afterward, the analysis was proceeded for the post-COVID-19 period, for which the assumptions have already been checked in Table 1. The fit measurement results for the post-COVID-19 model are presented in Table 7.

Table 7. Fit measurements of the post-COVID-19 models

	Overall Model Test					Omnibus Likelihood Ratio Tests			
Models	**-2LL**	R_N^2	χ^2	**df**	**p**	**Predictors**	χ^2	**df**	**p**
Post-COVID-19-1 (PoC-1)	337	0.646	367	3	< .001	Seat comfort	14.6	1	< .001
						Cabin staff	51.3	1	< .001
						Ground service	49.7	1	< .001
Post-COVID-19–2 (PoC-2)	221	0.766	441	1	< .001	Value for money	441	1	< .001

Accordingly, both model is statistically significant (PoC-1: $\chi^2(3, 684)$: 367, -2LL: 337, p < .001; PoC-2: $\chi^2(1, 684)$: 441, -2LL: 221, p < .001). According to Nagelkerke R^2, the PoC-1 model explains 64.6% of the variance in value for money in the post-COVID-19 period. Additionally, value for money explains 76.6% of the variance in overall satisfaction in the same period. Table 8, indicating the classification of the post-COVID-19 models, suggests that both post-COVID-19 logistic models has more than 90% overall success in classification.

Table 8. Classification table of the post-COVID-19 models

Models	Observed	Predicted		Performance
PoC-1		**Non affection**	**Affection**	**% Correct**
	Non affection	528	12	97.8
	Affection	42	102	70.8
	Overall percentage			92.1
PoC-2				
		Disconfirmation	**Satisfaction**	**% Correct**
	Disconfirmation	531	24	95.7
	Satisfaction	9	120	93.0
	Overall percentage			95.2

Table 9 presents the results of binominal LRA regarding the post-COVID-19 models.

Table 9. Logistic regression results of post-COVID-19

Model Outcomes: Value for money in PoC-1, Satisfaction in PoC-2							95% Confidence Interval	
Model	**Predictor**	**Estimate**	**SE**	**Z**	**p**	**Exp (β)**	**Lower**	**Upper**
PoC-1	Intercept	-3.10	0.206	-15.04	< .001	0.045	0.030	0.067
	Seat comfort (X_1): Affection – Non affection	1.57	0.415	3.78	< .001	4.797	2.128	10.812
	Cabin staff (X_2): Affection – Non affection	2.30	0.310	7.41	< .001	9.980	5.431	18.339
	Ground service (X_3): Affection – Non affection	2.50	0.363	6.87	< .001	12.141	5.958	24.739
PoC-2	Intercept	-4.08	0.336	-12.1	< .001	0.016	0.008	0.032
	Value for money (X_4): Affection – Non affection	5.69	0.404	14.1	< .001	295.000	133.727	650.765

Accordingly, the contributions of all predictors on value for money and satisfaction are statistically significant for both models (p< .001). So, the logit equations of the models are proposed in Equations (5) and (6).

$$Logit(value\ for\ money) = -3.10 + 1.57X_1 + 2.30X_2 + 2.50X_3 \quad (5)$$

$$Logit(satisfaction) = -4.08 + 5.69X_4 \quad (6)$$

According to Table 9, all variables have Exp (β) higher than 1. So, the most potent predictor of value for money is ground service, having a 12.141 odds ratio. It means that high perceived quality belonging to ground service increases the likelihood of value for money by 12.141 times (Δodds= + 1114%). Similarly, higher perceived quality of cabin staff and seat comfort services increases the likelihood of perceiving higher value for money by 9.980 (Δodds= + 898%) and 4.797 (Δodds= + 379%) times, respectively. In addition, according to the PrC-2 model, high value for money perception increases the likelihood of passengers being satisfied by 295 times (Δodds= + 29400%). The ROC curves are illustrated in Figures 8 and 9, and predictive measures of the models are reported in Table 10. Similar to the pre-COVID-19 models, the curve is quite close to the upper left, which means the discrimination powers of both post-COVID-19 models are high. Moreover, the models PoC-1 and PoC-2 have an AUC value of more than 0.90, confirming the performances of the models are perfect.

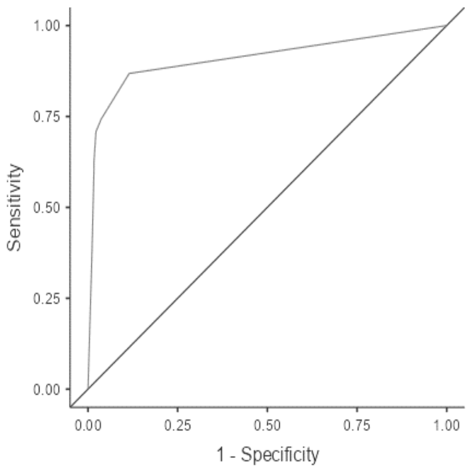

Figure 8. ROC curve for PoC-1 model

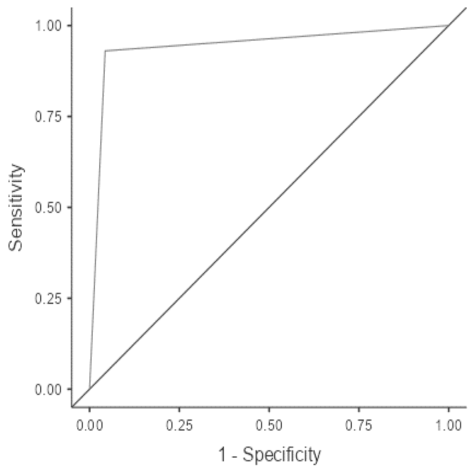

Figure 9. ROC curve for PoC-1 model

Table 10. Predictive measures of the PoC models

Models	Accuracy	Specificity	Sensitivity	AUC
PoC-1	0.921	0.978	0.708	0.909
PoC-2	0.952	0.957	0.930	0.943

5. Discussion and Conclusion

With the help of liberalization, competition in passenger markets was reshaped by LCCs, which had gained a noteworthy mark on domestic markets that once were dominated by full-service carriers (O'Connell & Williams, 2005). Thus, ticket prices have fallen, and air transportation has become more accessible (Zhang et al., 2007). In addition to dropping ticket prices, increased competition brought the service quality to the fore (Fu et al., 2010). Air carriers strive to enhance their market share by concentrating on service quality, the core driver for obtaining sustainable competitive advantage (Perçin, 2018). On the other hand, the primary way for airlines to improve their service quality is by thoroughly understanding passengers' expectations and perceptions. Nowadays, user-generated content (UGC), which is easily accessible on the internet, offers significant opportunities for airlines to gain insights that help them better understand their passengers and achieve a competitive advantage. Therefore, this research contributes particularly to airlines adopting the short-haul low-cost carrier business strategy by providing literature contributions and managerial implications.

Upon examination of the results, it is evident that seat comfort, cabin staff, and ground service significantly impact value for money ($p < .001$), as well as value for money on passenger satisfaction ($p < .001$). Consequently, all the hypotheses were supported for both COVID-19 periods. LCCs are trying to attract passengers with sensitivity toward value for money (Rajaguru, 2016). In line with this, Kusumawardani and Aruan (2019) revealed that the prediction power of the value for money on satisfaction is higher on LCCs than on full-service carriers. So, our findings regarding the value for money, a core service attribute, are consistent with the literature. Even though seat comfort is traditionally regarded as more critical for long-haul flights (Warnock-Smith et al., 2017), Punel et al. (2019) revealed that seat comfort is the most influential factor in perceived value for money across all travel classes, including business, first, and economy class in Europe. In fact, it is the primary inflight service attribute considered by economy class passengers in Europe. Our results suggest that seat comfort is one of the significant predictors of the value for money, regardless of flight-haul. Cabin staff and ground services are other critical factors consistently handled for evaluating airline service quality (Chen & Chao, 2015; Kim & Park, 2017; Medina-Muñoz et al., 2018). Sezgen et al. (2019) concluded that friendly staff is the joint driver of satisfaction regardless of passenger type. Moreover, ground service, which contributes to the passengers' safety perception (Shiwakoti et al., 2022) is one of the main themes in content analysis studies (Ban & Kim, 2019; Brochado et al., 2019), and is a significant service attribute for all passenger types (Brochado et al., 2022). Ismail and Jiang (2019) stated that ground service is noteworthy yet the least important factor for three long-haul LCCs: Scoot, Jetstar, and Air Asia X. According to Saha and Theingi (2009), ground service has no meaningful effect for Thai LCCs. Our study revealed that ground services and cabin staff services are more crucial drivers of value for money for short-haul LCCs in Europe.

The paper presents several managerial implications for short-haul LCCs. Our logit model indicates that ground service is the foremost determinant of the value for money. Accordingly, improving all the aspects of the ground services with a holistic perspective and eliminating existing problems can increase passengers' perception of the value for money in short-haul LCCs. In turn, passengers with high perceived value for money can become unpaid staff in your company's marketing department. The results suggest that the effect of the ground services and cabin staff services on the value for money has improved after COVID-19. Conversely, the impact of seat comfort on the value for money has downsized after the pandemic. However, it is important to note that the difference between the pre- and post-COVID-19 periods is not considered statistically significant, as all established models have overlapping confidence intervals (Morfeld et al., 2021).

This study has some limitations. Firstly, there is no consensus on when the post-COVID-19 begins. Therefore, the literature was referred to indicate the beginning of COVID-19 period. Secondly, Skytrax data was used, and the number of reviews in the post-pandemic period was relatively low, as illustrated in Figure 4. Additionally, the model variables were re-coded to create a dichotomy in passenger evaluations, classifying them as either non-affection/affection or disconfirmation/satisfaction, following the established procedures in the existing literature (Halpern & Mwesiumo, 2021). Also, it is noteworthy to recall that the structure of the industry and the nature of humans are quite dynamic. Therefore, passenger expectations may evolve over time, necessitating the introduction of new service quality criteria into the model. Future studies may explore a similar context with a holistic perspective, as demonstrated by Punel et al. (2019), incorporating various travel classes and traveler types. Considering similar studies using UGCs, bias in passenger reviews within the Skytrax database has been overlooked in the scope of the research. However, further investigation can be conducted on the bias in these reviews (Kerkhof & Münster, 2019). Moreover, a different methodology, such as structural equation modeling, sentiment analysis, or multi-criteria decision-making, might be used to analyze similar cases. Additionally, researchers could utilize TripAdvisor or other passenger review platforms as databases due to the extensive number of reviews available.

Statement of Research and Publication Ethics

Not applicable.

Declaration of Interest

The authors have no conflicts of interest to disclose.

Authorship Contribution Statement

Ferhat İNCE; Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Visualization. Emircan ÖZDEMİR; Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Visualization.

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