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How Can Service Convenience Reestablish Passenger Satisfaction After a Flight Delay? A Data Mining Approach

Olavo Pinto[*], Amélia Brandão[**], Mahesh Gadekar[***]

Abstract: The rapid development in aviation has transformed the way air travellers travel. Service failures, such as flight delays, significantly impact consumer satisfaction and its various dimensions. Consequently, flight delay has been identified as one of the critical factors in service failure. To improve satisfaction, airlines need to understand how consumer satisfaction can be enhanced in service failure incidents such as flight delays. As air travel recovers, understanding how service failures impact satisfaction and how they can be mitigated is crucial. Therefore, this study measures consumer airline satisfaction based on 129,880 observations of airline passengers (Study 1). It conducts data mining to predict that service convenience influences service failure perception (flight delay) and enhances consumer satisfaction (Study 2). The results indicate interesting trends. It is found that service convenience is the primary driver of delayed service failure recovery from the perspective of airline passengers. Airlines should invest in enhancing convenience and digital services, including virtual assistants, implementing automatic recovery mechanisms for flight delays, and considering the proximity of boarding gates to minimise walking distance.

Keywords: airline consumer satisfaction; flight delays; machine learning; data mining; service failure.

JEL classification: M1; M3.

[*] School of Economics and Management, University of Minho, Portugal; e-mail: *olavopinto@gmail.com* (corresponding author).
[**] School of Economics and Management, Cef.up, University of Porto, Portugal; e-mail: *ameliabrandao@fep.up.pt*.
[***] Indian Institute of Management, Jammu, India; e-mail: *maheshgadekar76@gmail.com*.

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1. INTRODUCTION

Researchers and managers are deeply interested in understanding how customer satisfaction can be maximised during service failure due to flight delays. A growing body of literature has demonstrated how service failure, such as flight delay, can have negative customer experiences, customer behavioural outcomes, and financial performance and market share (Zeithaml *et al.*, 1996; Keiningham *et al.*, 2014; Sembada *et al.*, 2016; Hall and Hyodo, 2022). Airline flight delays occur regularly and are a significant cause of customer dissatisfaction. For instance, in 2021-22, the airline's flights were delayed 26-29% of the time, while in 2019, 18.6% were delayed (Buchholz, 2023). Thus, researchers and managers must find solutions to recover from service failure.

While studies have focused on countermeasures toward service failures (Das *et al.*, 2020; You *et al.*, 2020), such as apologizing and compensating in mitigating consumer anger (McCollough, 2009; Cummings and Yule, 2020; Baliga *et al.*, 2021) research suggest that service failure is one of the significant causes of customer dissatisfaction leading to adverse business outcomes and improvement in customer satisfaction can help in gaining competitive advantage in the aviation industry (Noviantoro and Huang, 2022). Given the accessibility to capturing and recording visuals and social media presence, the incident of service failure sooner becomes part of the public domain, leading to a challenging situation for the airlines. We subscribe to the opinion (e.g., Kanuri and Andrews, 2019) that researchers need to gain access to large datasets to examine variables related to service failure and suggest how service failure recovery can be achieved, leading to better profitability and higher consumer satisfaction.

In the present research, we measure consumer airline satisfaction based on 129,880 observations of airline passengers and suggest that service convenience influences perceptions of service failure (flight delay) and enhances consumer satisfaction. The data used in the present research were gathered from the website Kaggle (Klein, 2020) and are freely available. This database was selected based on its large number of responses and has been previously used in data mining analysis, as noted by Park *et al.* (2019). Using the theoretical lens of cognitive appraisal theory (Lazarus, 1991), we demonstrate that airline consumers with improved service convenience will be more satisfied in the event of flight delay. Central to this effect is the cognitive appraisal theory that supports the importance of information processing and its impact on emotion (Skavronskaya *et al.*, 2021). Specifically, the theory demonstrates the mental process of evaluating inputs to determine the form of emotional reaction in each situation (Johnson and Stewart, 2004). Cognitive appraisal theory (Lazarus, 1991) and recent studies (e.g., Kleijnen *et al.*, 2007; Chekembayeva *et al.*, 2023), highlighted the role of convenience in explaining usage intention. This learning enhances our understanding of the importance of service convenience in improving consumer satisfaction.

By identifying the link between consumer satisfaction and service convenience during the service failure of the airlines, we contribute to the customer satisfaction literature in service failure incidents (e.g., Anderson, 1998; Anderson and Mittal, 2000; Hall and Hyodo, 2022; Pantano and Scarpi, 2022). Given that the airline industry is more prone to service failures, such as delays (Palmer and Bejou, 2016), this research contributes to the existing literature on service failures in the industry (Nazifi *et al.*, 2021). Furthermore, using a large dataset of complex and empirical data, we employed a data mining method to analyse airline passenger satisfaction, particularly in the context of flight delays, and provided solutions to offer accurate predictions. This approach aims to enhance our understanding of consumer satisfaction and mitigate negative responses to service failure incidents, such as flight delays.

2. CONCEPTUAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

This study proposes a conceptual model for measuring consumer satisfaction in the airline context. It examines how service convenience influences perceptions of service failure (such as flight delays) and enhances consumer satisfaction. In the first study, the present research employs three constructs to measure consumer satisfaction, contextualised for the airline customer, drawing on the literature (Nghiêm-Phú, 2019; Park, 2019; Kosiba *et al.*, 2020). The second study, using data mining analysis, is adopted to predict consumer satisfaction based on the factors previously analysed - Convenience, Service, and Functionality, employing data mining techniques and machine learning models to predict consumer satisfaction.

2.1. Customer satisfaction and airline service

Customer satisfaction is a crucial measure for companies, and a broad research subject is the expectation of service performance and its impact on attitude and patronage intention (Oliver, 1980). It enhances knowledge of consumer behaviour, branding, and the effectiveness of communication and marketing management. Customer satisfaction measurement has undergone multiple developments and is utilised by practitioners across various industries and researchers. Moreover, when the company meets and exceeds customers' expectations, it increases customer loyalty (Chen and Chen, 2010) and repurchase intention (Park *et al.*, 2019).

Based on previous literature, this research employed three constructs to measure consumer satisfaction through the lens of airline customers (Nghiêm-Phú, 2019; Park, 2019; Kosiba *et al.*, 2020). Satisfaction is assessed using a 5-point Likert scale, consistent with previous studies (Anderson, 1998; Park *et al.*, 2019)

The first dimension, convenience, encompasses in-flight Wi-Fi, arrival and departure times, online booking ease, and gate location; notably, in-flight Wi-Fi was found to be insignificant for overall satisfaction (Nghiêm-Phú, 2019). The second dimension, service satisfaction, relates to the flight experience and covers in-flight service, onboard assistance, baggage handling, and legroom. The third dimension, functionality, focuses on seat comfort, food and drink quality, and cleanliness.

Satisfaction within the airline industry is a growing area of research. The airline industry's travel market is a mature one in most regions of the world, a truly global business, and competition strives to retain recurring customers through convenient online services (Park *et al.*, 2019). Moreover, airlines face high levels of competition, and prioritising customer satisfaction is crucial for retaining existing customers (Park *et al.*, 2019). Because the memory of past experiences influences satisfaction, a continuous relationship with airline brands is crucial (Lin, 2015). In the airline industry, customer satisfaction and loyalty are jointly affected by service quality and perceived value (Nghiêm-Phú, 2019). Studies related to airlines have identified various factors impacting airline satisfaction. For instance, airline service quality is linked to comfort, in-flight experience, physical experience, and interaction during the flight, ultimately influencing service quality (Vázquez-Casielles *et al.*, 2007; Nghiêm-Phú, 2019).

Prior studies on airline satisfaction have identified the determinants of customer satisfaction. However, these studies represented respondents who volunteered for the research, with a sample size of less than 1000. Large-scale studies were also conducted that analysed extensive customer datasets. For instance, Park *et al.* (2019) investigated the potential determinants of customer-perceived satisfaction from large datasets. This study finds large-scale customer datasets to examine determinants of customer satisfaction in specific service failures.

2.2. Service convenience

Service convenience is one of the critical determinants of customer behaviour and its role in influencing service quality and fairness (Srivastava and Kaul, 2014). Additionally, prior studies have identified service convenience dimensions that lead to improved customer perception of convenience. Because modern life and stress affect consumers in terms of time commitment, firms are expected to ensure that the services are time-saving and effortless (Lloyd *et al.*, 2014; Malhotra *et al.*, 2016). Improved service convenience affects customer engagement and overall service quality (Nguyen *et al.*, 2012). In the airline industry, service convenience refers to the environment where customers can easily and comfortably experience service and access convenient facilities (Bezerra *et al.*, 2016). Because the service associated with the airline is inseparable, requiring passengers to travel to the airport before the flight's departure physically, the consumer perception is related to various dimensions of service convenience. Specifically, consumers prefer better interactional services and service-related air travel. Similarly, airline passengers may express dissatisfaction due to the need for more WiFi facilities and in-flight entertainment (Nurhadi *et al.*, 2019).

2.3. Airline flight delay

Flight delay has attracted the attention of researchers. Because passengers' expectations of flight on-time arrival have increased, it is one of the sources of competitive advantage (Yimga, 2017). When a flight is delayed, it affects both the firm's performance and society as a whole. Statista (2025) states that flight claim companies had an economic impact of $ 208 million in Europe and North America. Consequently, flight delays affect air passengers' intention to travel again and retail spending (Fuerst *et al.*, 2011; D'alfonso and Nastasi, 2014).

Prior studies supported that the comparison of performance satisfaction between a low cost and is subject to different levels and dimensions of Satisfaction (Lin, 2015) but not for how customer class, between Business, Economy, and Economy Plus, play in different types of satisfaction with the service, while first-class and Business seem to be similarly levelled (Hwang and Lyu, 2018). In addition, the distance of flights in the industry is categorised as short-haul, medium-haul, and long-haul, according to the ranges provided by European regulators (Eurocontrol, 2018), and is often delayed in real-world scenarios. The different dimensions presented here, with the convenience and comfort provided in flight and the interaction with the airline, may have different satisfaction behaviours depending on the flight distance. A more convenient gate may be significant for a short business trip taken frequently, but less critical for a long-haul vacation trip. Moreover, the data analysis enables us to pinpoint when there is a delay in both departure and arrival. European legal procedures were used to determine a delay, which lasted from 30 minutes to 6 hours, after which it may be considered a cancellation (EUR-Lex, 2007). The departure and arrival are determined, and the perceptions of satisfaction are registered. The different dimensions of satisfaction were analysed by comparing different delay ranges and no delay. It is expected to have a negative relationship proportional to the increasing level of delay the flight takes. Despite this, external variables may explain the different performances of customer attention, service recovery, and compensation, among others (Vázquez-Casielles *et al.*, 2007). Nevertheless, delay, one of the leading causes of customer complaints about airline services, is expected to have a role in customer satisfaction.

Furthermore, flight delays are one of the most common causes of complaints from airline customers (Mohd-Any *et al.*, 2019). Despite this, the literature suggests that training may find an optimised way to manage the incident, reading the emotional and cognitive assessment of the situation made by the customer (Vázquez-Casielles *et al.*, 2007). Additionally, regarding innovative brand experience research, schedule ranks first among the antecedents of service quality, followed by flight staff, tangibles, and ground staff (Lin, 2015). The level of satisfaction compared to the behaviour of a delay when recovered during flight, when the delay worsened during flight, and when the delay remained constant is a first approach to effective service recovery based on factual data and customer satisfaction in different dimensions.

Thus, we hypothesise that:

H1*: Satisfaction dimensions positively relate to the business customer class.*

H1.1*: Convenience dimension positively relates to the business customer class.*

H1.2*: Service dimension positively relates to business customer class.*

H1.3*: The Functionality satisfaction dimension positively relates to the business customer class.*

H2*: Satisfaction dimensions are positively related to flight distance.*

H2.1*: Convenience dimension is positively related to flight distance.*

H2.2*: Service dimension is positively related to flight distance.*

H2.3*: Functionality dimension is positively related to flight distance.*

H3*: The delay type at different points in time negatively impacts passengers' satisfaction dimensions.*

H3.1*: Convenience dimension is positively related to delay type at different points in time.*

H3.2*: Service dimension is positively related to delay type at different points in time.*

H3.3*: Functionality dimension is positively related to delay type at different points in time.*

H4*: A Recovery will have a positive and significant relationship with delay types.*

3. STUDY 1: DIMENSIONS OF AIRLINE SATISFACTION AND RELATIONSHIPS FROM BIG DATA

This first study aims to present the conceptualisation of customer satisfaction in the airline industry context and explore the different relationships with service performance. According to the extant literature, the typification of constructs is based on various dimensions of airline service provision. It is on the characterisation of the contextual airline service that the present research advances the components of customer satisfaction regarding service failure and demographics. A complete dataset was used to analyse based on the dimensions mentioned above.

The many observations present an opportunity to research consumer satisfaction in the airline context. Afterwards, the conceptual model is emphasised based on the extant literature, including both theoretical and empirical studies. Firstly, a multivariate procedure, Exploratory Factor Analysis, enabled us to identify the dimensions that contribute to customer satisfaction in the present dataset within the given context. Despite this, several considerations were developed regarding the context and previous theory, enabling the establishment of a relevant and valid model, as well as the respecification of the constructs' validity (Byrne, 2013).

Using various statistical tests, multiple evaluations were conducted to enhance the robustness and validity of the model. Covariance errors improved the model fit by addressing high scores in modification indices, as observed through the analysis of extreme outliers in the Mahalanobis distance (Byrne, 2013). Only after these considerations add robustness and validity to the conceptualisation of the model, the present research employs a Confirmatory Factor Analysis to test the proposed hypothesis (Brown, 2015), which addresses a novel and, to the author's knowledge, previously untested aspect in the extant marketing and tourism literature. A Structural Equation Modelling analysis was performed by using Amos.

3.1. Descriptive

Regarding delays, according to the U.S. Department of Transportation, the Transportation system had some delays in December 2019, which is in line with other periods (Department of Transportation's Office, 2019). According to previous studies, delays are often the leading cause of customer complaints. A plane is considered on time when it arrives at its destination within 15 minutes of the scheduled time, most of the time in U.S. and European markets (Department of Transportation's Office, 2019; Klein, 2020). The data collected pertains to each respondent's observations of departure and arrival delays. This method provided a detailed measurement of the delays experienced at both departure and arrival points. Specifically, it facilitated the analysis of delays considering regulatory provisions, helping to identify ranges of low, medium, and high delays for both departures and arrivals based on the average levels of compensation provided (EUR-Lex, 2007), as characterised in Table no. 1.

Table no. 1 - Classification of Flight Delays by Time Interval

Type of Delay	Time
No delay	0 to < 30m
Delay	30m to < 2h
Medium Delay	Two h to < 5h
High Delay	≥ 5h

The data used in the present research were gathered from the website Kaggle (Klein, 2020) and are freely available for anyone to use. The dataset contained 129.880 observations of airline passengers, of which 50.7% are female. Loyalty is described in the database as customers who reuse the airline's services, and those represent 81.7% of the observations. The age distribution is presented in Figure no. 1, using the same range as in previous research (Prentice, 2019).

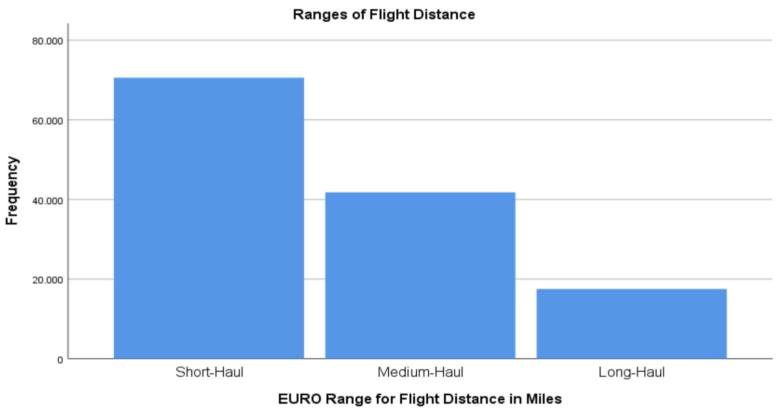
The travel type and class are variables to consider when analysing airline consumers. For the class, airlines often offer different ranges commonly allocated to other areas of the aeroplane. Each type of service typically provides differentiation in food, ambience, and entertainment, as well as a strategic location for faster seating and departure, and other amenities that can enhance the overall experience. In the dataset, these were ranked by frequency as Business (47.9%), Economy (44.9%), and Economy Plus (which offers a spacious seat), with the latter having a relatively low representation (7.2%). The type of travel describes the purpose of the trip the customer makes, with 69.1% for business purposes and 30.9% for personal/leisure reasons.

Most of the observations on the dataset did not present any delay in departure or arrival in 85.4% of the cases. According to European delimitations, and as previously stated, this corresponds to no delay on departure that's less than 30 minutes. After this, the dataset has 12.1% cases of delay. Only 2.3% of the delays go between 2 and 5 hours. After six hours, the airline must provide total compensation in accordance with European regulations. This is uncommon, and 313 observations are available in this dataset. This is 0.2%, which is a small amount.

Using the available data, a differential was calculated regarding the performance of the delay, measuring the placement in the range of delay differential between the departure and arrival of the flight. This would create scenarios based on actual flight time data, which would maintain, worsen, or recover from a delay. For this, the frequencies in the data represent 83.2% of no delay at all. However, for those who experienced a delay at departure, 11.4% would be in the same delay range on arrival. However, there are many observations where this delay would worsen after departure (2.9%), and in these cases, the delay would be compensated (2.5%). For example, some flights where the departure would cause a delay at the low end would eventually compensate during the flight.

In defining the distance travelled, the maximum ranges of 1,500 km for short-hauls and 4,000 km for medium-hauls were adopted (Eurocontrol, 2018), cataloguing the observations in this way, even though this may not apply to every region due to its specificities. The dataset presented the distance travelled by the respondent, and using the range mentioned earlier, 54% of the observations were in the short-haul distance. Medium-haul travels were 32.2%, and long-haul represented only 13.5% of the observations.

Table no. 2 presents all the component variables available in the dataset for customer satisfaction with airline services. It includes the item mean, the standard error, skewness, and kurtosis for all the variables. These used a 1-5 Likert scale, similar to research with customer satisfaction concepts (Lin, 2015; Antwi *et al.*, 2020; Kosiba *et al.*, 2020). In the present study, these items were allocated to 3 different dimensions of constructs, using at least three items each. This decision was made using available knowledge from previous theories and literature, as well as an exploratory factor analysis.



Source: authors' contribution

Figure no. 1 – Ranges of Flight Distance

Table no. 2 – Components of consumer satisfaction

Item	Mean	SE	Skewness	Kurtosis
Inflight WiFi service	2.81	1.359	-0.25	-1.159
Departure/Arrival time convenient	3.22	1.281	0.123	-1.039
Online booking	2.88	1.278	-0.058	-1.032
Gate location	2.98	1.326	-0.149	-1.158
Food and drink	3.21	1.253	-0.344	-0.907
Online boarding	3.33	1.319	-0.486	-0.923
Seat comfort	3.44	1.333	-0.366	-1.063
Inflight entertainment	3.36	1.287	-0.421	-0.89
Onboard service	3.38	1.298	-0.318	-1.055
Legroom service	3.36	1.18	-0.677	-0.384
Baggage handling	3.63	1.266	-0.367	-0.83
Check-in service	3.31	1.176	-0.691	-0.36
Inflight service	3.64	1.313	-0.3	-1.016
Clean	3.29	1.244	0.162	-0.959

Source: authors' contribution

Additionally, a binary variable distinguishes between satisfied and unsatisfied customers, in conjunction with the constructs presented. Table no. 3 presents the frequency of those observations in the dataset.

Table no. 3 – Frequency of Satisfaction vs. No Satisfaction

Item	Frequency	Per cent
Not Satisfied	73.452	56.6%
Satisfied	56.428	43.4%

Source: authors' contribution

3.2. Principal component analysis

The previous conceptualisation of satisfaction with airline services was considered for the development of the present study. Additionally, the exploratory factor analysis performed on the large dataset allowed for a test of the most significant factors influencing customer satisfaction.

After several EFA, the final model is provided by Principal Component Analysis, with the rotation method Varimax with Kaiser Normalisation. The first factor in the final model is convenience, which explains 22.67% of the variance and has four components with factor loadings ranging from .747 to .874. Next is a service that explains 22.26% of the total variance, characterised by four elements, with factor loadings ranging from 0.633 to 0.839. Finally, Functionality. Functionality explains 20.93% of the variance and consists of 3 items with factor loadings ranging from .854 to.892 These three factors explain 65.66% of the model's total variance.

Table no. 4 – Factor loadings and commonalities from a principal component analysis with rotation method varimax for 11 items

Item	Convenience	Service	Functionality
Online booking	0.874		
WiFi Inflight	0.767	0.139	0.170
Time Conve.	0.759		
Gate Location	0.747		
Inflight Serv.		0.839	
Baggage		0.827	
Onboard Serv.		0.787	
Leg Room		0.633	
Clean			0.892
Seat Comfort			0.857
Food & Drinks			0.854

Note: Factor loadings < 0.1 are omitted.

Source: authors' contribution

After an inspection of the Homogeneity of Variances, Tamhane's variance analysis was performed due to Levene's test failure. A Principal Component Analysis uncovered the components of the final model, saving the regression factor scores into new variables. The Kaiser-Meyer-Olkin Measure (KMO) and Sample Adequacy are very good, with a value of 0.787, which is above the recommended value of 0.6. Anti-image – Measures of Sample Adequacy (MSA) indicate that all diagonals are well above the recommended value of 0.5, with the lowest being 0.672 for "Ease of Booking Online" and the highest being 0.848 for "Leg Room". Additionally, Bartlett's Test of Sphericity performed well ($\chi2$ (55) = 506497, p < .001). When performing further adjustments to the model, excluding Online boarding, in-flight Entertainment, and Check-in service, the KMO value signals 0.741.

Table no. 5 – Regression Analysis Results

Item	β	t	p	R^2_a	VIF
Convenience F(4,129875)=10280017	-	-	***	**.997**	
Online	.363	1507	***	-	2.4
Gate Location	.310	1629	***	-	1.5
Time Convenience	.302	1568	***	-	1.5
WiFi Inflight	.285	1323	***	-	1.9
Service F(4,129875)=5276489	-	-	***	**.994**	
Inflight Service	.348	1164	***	-	1.9
Baggage Handling	.343	1170	***	-	1.8
Onboard Service	.323	1182	***	-	1.5
Leg Room Service	.258	1069	***		1.2
Functionality F(3,129876) = 5081207	-	-	***	**.992**	
Clean	.383	986	***	-	2.3
Food & Drinks	.385	1104	ns	-	1.9
Seat Comfort	.374	1045	ns	-	2.0

Note: *** indicates p-value < .001, ** indicates p-value < .01, * indicates p-value < .05, ns = non-significant.

Source: authors' contribution

The dependent variables within the same construct underwent linear regression analysis for the final Model Proposed, as presented in Table no. 5. Concerning Multicollinearity, all the VIF values were two or well below that, which is very well below the 10-cut-off value proposed in the literature.

3.3. Reliability and validity

Factoring in different constructs, the satisfaction items are highly correlated and sufficiently distinct from one another, achieving statistical significance, thereby representing various dimensions of customer satisfaction in the airline industry. The correlation matrix within the construct is always positively correlated (Pearson Correlation > .5) and significant (p-value < .001).

Table no. 6 – Parameter estimates for the CFA model (Factor Loadings)

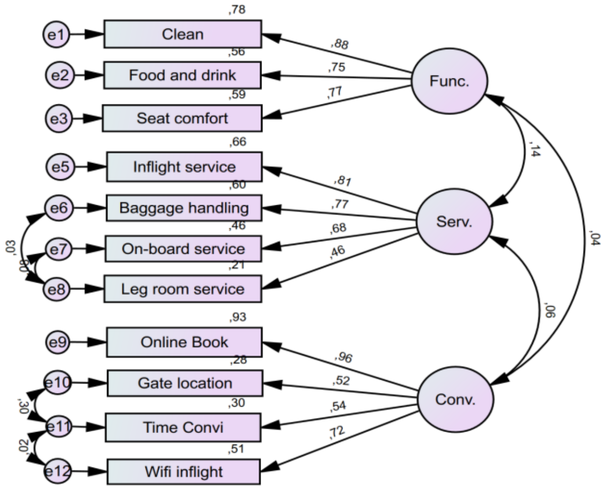
			Estimates	S.E.	C.R.	P
Regression weights						
Seat comfort	<---	Func.	.877	.003	274.77	***
Food and drink	<---	Func.	.853	.003	268.37	***
Cleanliness	<---	Func.	1.000			
Baggage handling	<---	Serv.	1.000			
Inflightwifiservice	<---	Conv.	.723	.004	187.66	***
TimeConvenient	<---	Conv.	.600	.004	157.04	***
EaseofOnlinebooking	<---	Conv.	1.000			
Gate location	<---	Conv.	.544	.003	157.38	***
In-flight service	<---	Serv.	1.050	.005	225.14	***
Legroomservice	<---	Serv.	.658	.005	141.99	***

			Estimates	S.E.	C.R.	P
Regression weights						
Onboard service	<---	Serv.	.959	.004	215.52	***
Seat comfort	<---	Func.	.877	.003	274.77	***
Food and drink	<---	Func.	.853	.003	268.37	***
Cleanliness	<---	Func.	1.000			
Baggage handling	<---	Serv.	1.000			

Source: authors' contribution

A closer examination of the modification indices was conducted to improve the model, and the link between high M.I. errors within the same constructs was identified to enhance reliability. Further, the Check-in Service and Online Boarding failed to measure in a new construct due to the high correlation of the items with measures outside the factor. These three variables were dropped, and a goodness-of-fit of the model was achieved: $\chi2$ (37) = 14783.607, p-value < .001; CFI = 0.971; NNFI = 0.971; RMSEA = 0.055. The factor loadings for each variable are in Table no. 6.

The model proposed reached composite reliability (> .6), AVE (> .5), and Cronbach's α (> .7) as per Table no. 7.



Source: authors' contribution

Figure no. 2 – Measurement Model Results

Table no. 7 – Reliability and validity tests

	Cronbach's α (> 0.7)	CR (> 0.6)	AVE (> 0.5)
Functionality	0.841	0.843	0.6
Convenience	0.797	0.792	0.5
Service	0.775	0.782	0.5

Source: authors' contribution

Also, there is discriminant validity with no intercorrelation outside the factors and a high convergent validity in the proposed factors (> 0.69) (Table no. 8).

3.4. Results

Analyse Variances using One-Way ANOVA. The dependent variable used was the Recovery Delay, which we developed by combining the departure and arrival delays, given the significant number of occurrences in the dataset. It used a significance level of 0.05 (α = .05).

All the ANOVA tests were significant since they had a $p < .001$. This means a substantial difference between the proposed groups can be found in at least one relation.

Post-hoc tests were performed to investigate further the differences between groups following significant ANOVA tests. Levene's test was performed, and in everyone, it presented a $p < .001$, except for the Service with Delay Performance test, which offered a $p < .05$. In every situation, this required using a post hoc test in which the variances could not be assumed equal, so all the further tests used Tamhane's T2.

Table no. 8 – Convergent and Discriminant Validity Results

	CR	AVE	Conv.	Serv.	Func.
Conv.	0.792	0.5	0.71		
Serv.	0.782	0.5	0.06	0.69	
Func.	0.843	0.6	0.05	0.14	0.80

Source: authors' contribution

Business groups of customers consistently scored higher on all satisfaction constructs.

Between these two types of travel, the dataset shows a statistically significant difference as per one-way ANOVA in the Convenience dimension ($F(1, 129878) = 19.02$, $p < .001$) for Service ($F(1, 129878) = 564.58$, $p < .001$) and for Functionality ($F(1, 129878) = 1837.72$, $p < .000$).

The group of loyal customers provided by the dataset also proved to be significantly different from those who are not faithful to any airline. These customers present in the dataset show statistically significant differences between groups for convenience as per one-way ANOVA ($F(1, 129878) = 111.99$, $p < .000$) for Service ($F(1, 129878) = 11.57$, $p = .001$) and Functionality ($F(1, 129878) = 1543.22$, $p < .001$). This data shows that loyal customers are significantly more satisfied in every dimension measured.

After the initial analysis, two One-Way ANOVA results with post hoc tests further revealed which group had an impact on the direction of each dimension of satisfaction (dependent variable). First, Table no. 9 provides the one-way ANOVA for a class type and the range of distance travelled.

For class type, business, economy, and Economy plus groups, after performing one-way ANOVA, were determined to be significantly different in Convenience ($F(2, 129877) = 11.67$, $p < .001$), Service ($F(2, 129877) = 3840.68$, $p < .001$) and Functionality ($F(2, 129877) = 1895.40$, $p < .001$).

Table no. 9 – ANOVA Tamhane multiple comparisons table for customer class and travel distance

Independent	*Dependent*		
	Convenience	**Service**	**Functionality**
Cust. Class	*p*	*p*	*p*
Business & EcoPlus	0.944*n.s.*	< .001*	< .001*
Eco & Business	< .001*	< .001*	< .001*
Eco & EcoPlus	< .01**	< .001*	< .01**
	F(2, 129877) = 11.67, p < .001	F(2, 129877) = 3840.68, p < .001	F(2, 129877) = 1895.40, p < .001
Tr. Distance	**Convenience**	**Service**	**Functionality**
Short - Long	0.495*n.s.*	< .001*	< .001*
Medium - Short	< .001*	< .001*	< .001*
Medium - Long	0.715*n.s.*	< .001*	< .001*
	F(2, 129877) = 6.70, p < .001	F(2, 129877) = 609.52, p < .001	F(2, 129877) = 750.72, p < .001

Source: authors' contribution

Table no. 10 – ANOVA Tamhane multiple comparisons table for delay and delay performance

	Dependent		
	Convenience	**Service**	**Functionality**
Independent Delay	*p*	*p*	*p*
No Delay – Delay	< .001*	< .001*	< .001*
No Delay – Medium Delay	.136*n.s*	< .001*	< .001*
No Delay – High Delay	.604*n.s*	.316*n.s*	.765*n.s*
Delay – Some Delay	1*n.s*	.983*n.s*	579*n.s*
Delay – High Delay	.203*n.s*	1*n.s*	1*n.s*
Some Delay – High Delay	.197*n.s*	.998*n.s*	.997*n.s*
	F(3, 129876) = 7.79, p < .001	F(3, 129876) = 52.52, p < .001	F(3, 129876) = 33.77, p < .001
Delay Performance	**Convenience**	**Service**	**Functionality**
Maintain - Recover	.816*n.s.*	.242*n.s.*	.657*n.s.*
Maintain - Worsen	.996*n.s.*	.826*n.s.*	1*n.s.*
Maintain – No Delay	< .001*	< .001*	< .001*
Recover - Worsen	.995*n.s.*	.076*n.s.*	.752*n.s.*
Recover – No Delay	.948*n.s.*	< .01**	< .05***
Worsen – No Delay	.438*n.s.*	< .001*	< .001*
	F(3, 129869) = 6.63, p < .001	F(3, 129869) = 55.59, p < .001	F(3, 129869) = 34.31, p < .001

Source: authors' contribution

Due to being proven significant, a Tamhane post hoc inspection uncovered that satisfaction with convenience was significantly higher for Business ($p < .001$) and Economy Plus ($p < .01$) compared to Economy. No statistically significant difference was found between Business and Economy Plus ($p = .994$).

In analysing service and functional satisfaction, the relationships between the two groups were statistically significant in both dimensions. On both Business ($p < 0.001$) and Economy Plus ($p < 0.001$), the fares were found to be higher and lower, respectively, than those of Economy. Business was also significantly higher ($p <0.001$) than Economy Plus.

About the range of distance travelled by the flight, according to the distances considered by European agencies, the One-Way ANOVA was found to be significantly different in all three dimensions: Convenience ($F(2, 129877) = 6.70$, $p < .001$); Service ($F(2, 129877) = 609.52$, $p < .001$) and Functionality ($F(2, 129877) = 750.72$, $< .001$).

The Tamhane T2 test, when analysing the Convenience satisfaction dimension, presented no statistically significant difference between either Short ($p = 0.495$) or Medium-haul ($p = 0.715$) and Long-haul. Medium-haul is significantly higher in satisfaction for convenience when compared to Short-haul ($p < .001$).

The post hoc test for distance travelled on service satisfaction and functional satisfaction shows that the relationships between the two groups were statistically significant in both dimensions. On both, Short-haul ($p < .001$) was found to be lower, and Long-haul ($p < .001$) was found to be higher, regarding Medium-haul travel distances. Long-haul travel was also significantly higher ($p < .001$) than short-haul travel on the Service and Functional Satisfaction dimensions.

Four different measures of delay typified as no delay, delay, medium Delay, and high Delay, the one-way ANOVA were determined to be significantly different in Convenience satisfaction($F(3, 129876) = 7.79$, $p < .001$), Service satisfaction ($F(3,129876) = 52.52$, $p < .001$) and Functionality satisfaction ($F(3, 129876) = 33.77$, $p < .001$). After a Tamhane post hoc inspection revealed that the satisfaction with Convenience, Service, and Functionality was significantly higher for No Delay ($p < .001$) compared to the first level of delay, no statistically significant difference was found between any other relation in Convenience Satisfaction, with all $p > .05$. For satisfaction with Service and Functionality, however, No Delay is significantly higher ($p < .001$) than Medium Delay. As shown in Table 10, no other group comparison is statistically significant ($p > .05$).

One-way ANOVA was also used to find significant differences between delay performances based on the previously defined ranges (Table 10). All the three factors where significant: Convenience ($F(3,129869) = 6.63$, $p < .001$); Service ($F(3,129869) = 55.59$, $p < .001$) and Functionality ($F(3,129869) = 34.31$, $p < .001$).

The Tamhane T2 test, when analysing the Convenience satisfaction dimension, presented no statistically significant difference between 'Recover' ($p = .816$) and 'Worsen' ($p = .996$) and 'Maintain the Delay'. There is also no statistically significant difference when comparing Recover ($p = .995$) with Worsen delay Maintain the Delay, nor with Recover ($p = .948$) and Worsen (0.438) and No Delay.

For the Service Satisfaction dimension, there was no statistically significant difference between Recover ($p = 0.242$), Worsen ($p = 0.826$) and Maintain the Delay. There is also no statistically significant difference when comparing Recover ($p = .076$) with Worsen delay.

Similarly, there was no statistically significant difference in functionality satisfaction between Recover ($p = .657$) and Worsen ($p = 1$) and Maintained the Delay. Also, there is no statistically significant difference when comparing Recover ($p = .752$) with Worsen delay.

The Tamhane post hoc test, when analysing the three dimensions, convenience, service, and functionality satisfaction, all proved to be significantly lower on Maintain ($p < .001$) compared to No Delay.

The same is true for Service satisfaction and functionality satisfaction, where "Recover" ($p < .01$) and "Worse" ($p < .001$ and $p < .05$, respectively) are significantly lower than "No Delay."

The present test revealed no significant difference in the tendency for recovery or worsening delays during flights. However, there is a substantial difference between those delayed flights and those that depart on time.

3.5. Findings & Discussion

Approaching a real and immense customer satisfaction database presents an opportunity to further conceptualise the dimensions present in the airline industry. Data showed that satisfaction is higher for business customers than for economy class. Economy Plus has higher satisfaction ratings than Economy in terms of convenience and functionality, but lower satisfaction with service. Satisfaction increases in service and functionality as the travel distance increases, except for convenience satisfaction, which drops in satisfaction from short to medium haul. The customer satisfaction regarding convenience is not significantly different for long-haul travel distances. There is a significant difference between those flights with delays and those that depart and arrive on time, supporting the fact that all dimensions of satisfaction have a significant negative relationship with delay.

Table no. 11 – Summary of Hypotheses Testing Results

Hypothesis	Observations	Test result
H1.1	Convenience dimension positively relates to business customer class	Not Supported
H1.2	Service dimension positively relates to business customer class.	Supported
H1.3	Functionality satisfaction dimension positively relates to business customer class.	Supported
H2.1	Convenience dimension is positively related to flight distance.	Not Supported
H2.2	Service dimension is positively related to flight distance.	Supported
H2.3	Functionality dimension is positively related to flight distance	Supported
H3.1	The type of delay negatively impacts passengers' Convenience dimensions	Not Supported
H3.2	The type of delay negatively impacts passengers' Service dimensions	Not Supported
H3.3	The type of delay negatively impacts passengers' Functionality dimension	Supported
H4	A Recovery will have a positive significant relationship with types of delay.	Not Supported

4. STUDY 2: DELAY SERVICE FAILURE DATA MINING PERFORMANCE

This study is followed by a data mining analysis that aims to predict user satisfaction based on the previously analysed factors: Convenience, Service, and Functionality, employing data mining techniques and machine learning models to predict consumer satisfaction. The analysis performed the following tests: Logistic Regression, Gaussian Naive Bayes, K-Nearest Neighbours, Decision Tree Classifier, Random Forest Classifier, Gradient Boosting Classifier, Multi-layer Perceptron (MLP) Classifier, and Support Vector Classifier (SVC), and evaluation metrics with Accuracy, ROC-AUC, F1 Score, Precision, and Recall. Measuring Delay Differential as a predictive performance indicator, the relationships between the three factors become more evident. The analysis utilises 20,353 records, representing 16% of the total observations in the original dataset, and considers only occurrences with positive Delay Differential, excluding those without this service failure.

The correlation matrices, representing variables with higher negative correlations in blue and those with stronger positive correlations in red, are presented in Figure no. 3. This allowed us to understand the patterns and dependencies of the factors in the dataset.

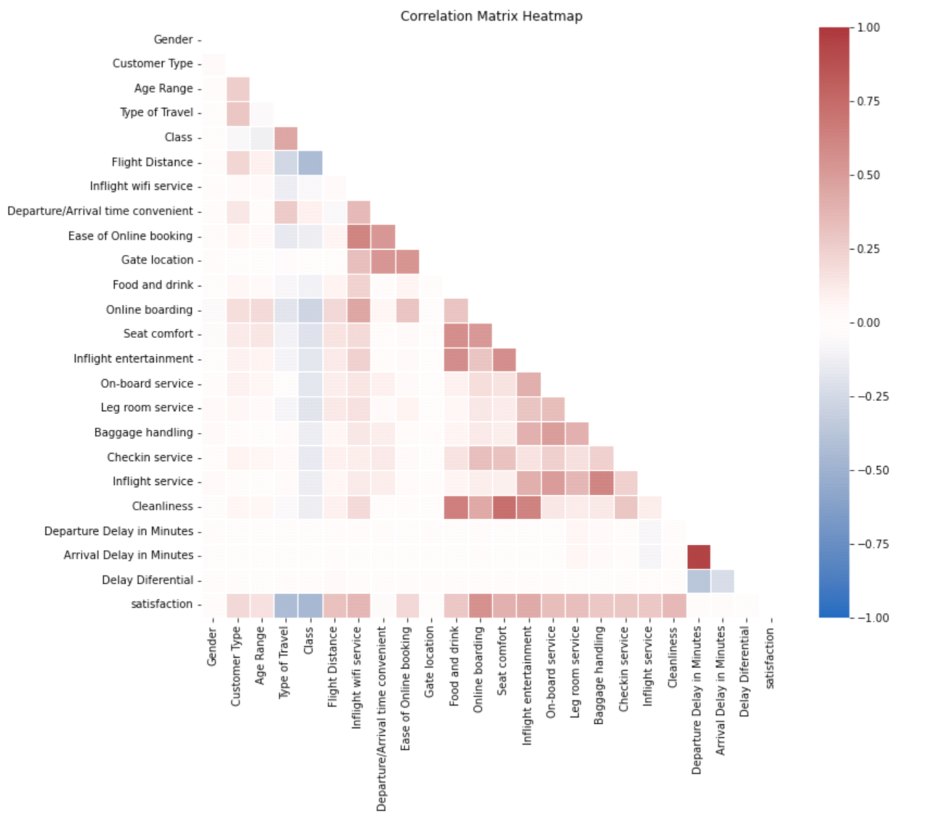


Figure no. 3 – Correlation Matrix

To predict user satisfaction, machine learning models were trained and evaluated using the Convenience, Service, and Functionality factors. Tables no. 12 and no. 13 present the results of the regression analysis. Table no. 12 represents the predictive performance without the "delay differential" feature, while Table no. 13 includes it. Including the "delay differential" feature negatively impacted the predictive performance of the analysis, highlighting model-building limitations for future research.

Table no. 12 – Regression without delay differential [Out 36]

	Factor	Model	Accuracy	Roc-Auc	F1	Precision	Recall
0	Convenience	LogisticRegression	71.64%	65.28%	54.56%	62.34%	48.52%
1	Convenience	GaussianNB	73.56%	68.16%	57.19%	66.22%	50.33%
2	Convenience	KNeighborsClassifier	85.64%	75.95%	79.08%	80.36%	78.53%
3	Convenience	DecisionTreeClassifier	87.60%	87.12%	82.99%	80.07%	86.13%
4	Convenience	RandomForestClassifier	87.58%	87.15%	82.97%	80.00%	86.27%
5	Convenience	GradientBoostingClassifier	87.47%	87.21%	82.97%	79.33%	86.97%
6	Convenience	MLPClassifier	87.59%	87.14%	82.98%	79.96%	86.29%
7	Convenience	SVC	87.02%	86.83%	82.70%	77.73%	88.35%

	Factor	Model	Accuracy	Roc-Auc	F1	Precision	Recall
8	Service	LogisticRegression	75.10%	71.56%	60.40%	68.30%	54.22%
9	Service	GaussianNB	76.93%	76.96%	68.88%	65.33%	72.90%
10	Service	KNeighborsClassifier	83.06%	81.68%	74.40%	78.76%	70.67%
11	Service	DecisionTreeClassifier	84.28%	81.01%	76.41%	79.85%	73.39%
12	Service	RandomForestClassifier	84.47%	81.84%	76.90%	79.39%	74.47%
13	Service	GradientBoostingClassifier	83.49%	81.32%	75.51%	78.16%	73.32%
14	Service	MLPClassifier	85.17%	81.66%	77.28%	82.57%	72.62%
15	Service	SVC	84.27%	81.49%	76.25%	80.23%	73.00%
16	Functionality	Logistic Regression	74.13%	69.75%	59.42%	66.11%	54.01%
17	Functionality	GaussianNB	72.56%	72.33%	64.94%	58.79%	72.56%
18	Functionality	K Neighbors Classifier	78.48%	75.17%	64.58%	75.78%	56.45%
19	Functionality	DecisionTreeClassifier	80.81%	77.35%	71.25%	74.93%	68.03%
20	Functionality	RandomForestClassifier	80.91%	77.71%	71.50%	74.64%	68.75%
21	Functionality	GradientBoostingClassifier	80.11%	77.07%	69.91%	74.38%	65.97%
22	Functionality	MLPClassifier	80.57%	77.11%	71.00%	75.01%	67.77%
23	Functionality	SVC	79.16%	75.22%	67.17%	75.26%	60.69%

Table no. 13 – Regression with delay differential [Out 39]

	Factor	Model	Accuracy	Roc-Auc	F1	Precision	Recall
0	Convenience	LogisticRegression	70.59%	63.62%	52.03%	60.78%	45.64%
1	Convenience	GaussianNB	73.73%	68.27%	57.55%	66.58%	50.72%
2	Convenience	KNeighborsClassifier	85.00%	83.80%	79.06%	76.69%	82.65%
3	Convenience	DecisionTreeClassifier	87.31%	87.07%	82.77%	79.17%	86.76%
4	Convenience	RandomForestClassifier	87.36%	87.12%	82.78%	79.15%	86.91%
5	Convenience	GradientBoostingClassifier	87.37%	87.23%	82.85%	79.18%	86.90%
6	Convenience	MLPClassifier	87.52%	87.40%	83.10%	79.66%	86.45%
7	Convenience	SVC	86.16%	82.37%	80.96%	78.28%	84.28%
8	Service	LogisticRegression	75.74%	70.99%	61.86%	69.01%	56.13%
9	Service	GaussianNB	77.10%	76.27%	69.12%	65.55%	73.26%
10	Service	KNeighborsClassifier	81.47%	79.61%	71.34%	77.77%	65.96%
11	Service	DecisionTreeClassifier	83.50%	80.92%	75.62%	77.64%	73.99%
12	Service	RandomForestClassifier	83.96%	81.53%	76.54%	77.95%	75.13%
13	Service	GradientBoostingClassifier	83.46%	81.16%	75.71%	77.67%	74.01%
14	Service	MLPClassifier	85.13%	82.42%	77.14%	82.17%	72.77%
15	Service	SVC	83.78%	81.09%	75.75%	79.00%	73.07%
16	Functionality	LogisticRegression	74.42%	69.51%	59.79%	66.73%	54.28%
17	Functionality	GaussianNB	72.78%	72.35%	64.97%	59.23%	72.14%
18	Functionality	KNeighborsClassifier	75.72%	73.24%	67.42%	65.49%	71.11%
19	Functionality	DecisionTreeClassifier	79.86%	76.82%	69.24%	74.26%	65.07%
20	Functionality	RandomForestClassifier	80.02%	76.82%	69.86%	73.89%	66.63%
21	Functionality	GradientBoostingClassifier	79.99%	77.05%	69.47%	74.72%	65.02%
22	Functionality	MLPClassifier	80.07%	77.24%	69.93%	73.97%	67.82%
23	Functionality	SVC	78.63%	74.51%	66.40%	74.15%	60.19%

The results from Table no. 12 show the predictive performance of the models when the Delay Differential is excluded and not considered.

Table no. 14 – The predictive performance of the three factors

Factor	Accuracy	Roc-Auc	F1	Precision	Recall
Convenience	83.13%	80.86%	75.14%	74.94%	76.29%
Functionality	77.69%	74.69%	67.14%	70.30%	65.28%
Service	81.77%	79.25%	72.89%	75.84%	70.54%

Table no. 13 presents the Delay Differential and its impact on the predictive performance of the models. Results show a noticeable decrease in predictive performance compared to Table no. 1, suggesting that Delay Differential is irrelevant in predicting the factors under analysis.

Subsequently, a machine learning analysis was conducted, as represented in Tables no. 3 and no. 4. The model displays Accuracy, ROC-AUC, F1 Score, Precision, and Recall. Accuracy demonstrates the ability to predict user satisfaction, while the ROC-AUC suggests that the models' discrimination is satisfactory. The F1 Score reflects the performance between precision and Recall, where precision indicates the proportion of correct optimistic predictions, and Recall, the model's ability to identify valid positive instances. These display the predictive performance for Convenience, Service, and Functionality, considering a Delay Differential. Convenience has emerged as the most critical factor, accounting for over 80% of user satisfaction.

The results of Table no. 14 show the predictive performance of the three factors. Convenience achieved an accuracy of 83.13%, a ROC-AUC score of 80.86%, an F1 Score of 75.14%, a precision of 74.94%, and a recall of 76.29%. Functionality achieved an accuracy of 77.69%, a ROC-AUC score of 74.69%, an F1 Score of 67.14%, and a precision of 70.30%. The Recall was 65.28%. The service yielded an accuracy of 81.77%, a ROC-AUC score of 79.25%, an F1 Score of 72.89%, and a precision of 75.84%. The Recall was measured at 70.54%. The convenience factor has the highest accuracy and overall predictive capabilities among the three factors, indicating that the models perform well in assessing user satisfaction. The service factor is close to Convenience, with a Functionality factor that has relatively lower accuracy and predictive power.

Table no. 15 – The Delay Differential and the analysis for Convenience and Functionality

Factor	Accuracy	Roc-Auc	F1	Precision	Recall
Convenience	83.51%	80.61%	75.68%	75.75%	76.42%
Functionality	78.34%	75.21%	67.47%	71.86%	64.28%
Service	82.10%	79.69%	73.25%	76.57%	70.57%

Table no. 15 considers the Delay Differential, and the analysis for Convenience, Functionality, and Service factors only shows small changes, indicating that the feature has a limited impact on the model. The models achieved an accuracy of 83.51%, a ROC-AUC score of 80.61%, an F1 Score of 75.68%, and a precision of 75.75%, as well as a recall of 76.42%. Functionality achieved an accuracy of 78.34%, a ROC-AUC score of 75.21%, an F1 Score of 67.47%, and a precision of 71.86%, a recall of 64.28%. The service yielded an accuracy of 82.10%, an ROC-AUC of 79.69%, an F1 Score of 73.25%, a precision of 76.57%, and a Recall of 70.57%.

4.1. Findings & Discussion

These methods align with existing research on travel consumer satisfaction, utilising data mining and machine learning techniques to predict user satisfaction (Noviantoro and Huang, 2022). This fact lends credibility to the present and future findings, thereby validating the research conclusions. The analysis reveals the significance of user satisfaction prediction and emphasises the central role of convenience factors in influencing user experiences.

For the first time, the analysis incorporated Delay Differential as a feature, which contributed to a detailed and deeper analysis of consumer satisfaction in the travel industry. This highlighted the importance of Convenience factors in attaining flight features that enhance user experience and satisfaction impacts. A data-oriented managerial application can feature increased results. At the same time, future research can expand upon the present findings by exploring alternative features and analysing additional factors influencing user satisfaction. Extending this analysis to different datasets, industries, and contexts can enhance research validation and confirm applications.

5. GENERAL DISCUSSION & CONCLUSION

Given the importance of consumer satisfaction in the airline industry, studies have highlighted the consequences of customer dissatisfaction and adverse behavioural outcomes. Flight delays are one of the leading causes of complaints from airline customers (Mohd-Any *et al.*, 2019). Thus, improving customer satisfaction can help gain a competitive advantage in the aviation industry (Noviantoro and Huang, 2022). In this study, we measure consumer satisfaction based on 129,880 observations of airline passengers. The study employs three constructs to measure consumer satisfaction, contextualised for the airline customer, drawing on the literature (Nghiêm-Phú, 2019; Park, 2019; Kosiba *et al.*, 2020). The study utilises data mining analysis, employing data mining techniques and machine learning models to predict consumer satisfaction. The study used a machine learning model to predict customer satisfaction regarding flight delays. Service convenience was found to play a crucial role in enhancing customer satisfaction in service failure incidents.

The study makes three significant theoretical contributions. First, the study contributes to consumer satisfaction literature in the event of service failure incidents by demonstrating that service convenience enhances consumer satisfaction in the event of flight delays. Thus, this study complements earlier studies on service failure incidents (e.g., Nazifi *et al.*, 2021).

Second, because the airline industry is regarded as one of the most susceptible industries to service failure, enhancing consumer satisfaction in such a crisis is essential. The study contributes to previous research (e.g., Anderson, 1998; Anderson and Mittal, 2000; Hall and Hyodo, 2022; Pantano and Scarpi, 2022). Third, using a large dataset in Studies 1 and 2, the theory utilises complex and empirical data in the context of flight delays and provides predictions for enhancing satisfaction in service failure incidents within the airline industry. This approach is intended to improve our understanding of consumer satisfaction and reduce negative responses in service failure incidents, such as flight delays.

This paper has practical implications for the airline service industry, specifically in mitigating failures in service encounters, such as when a flight delay occurs during departure and/or arrival.

First, airline companies should invest in enhancing passenger satisfaction through increased convenience. Therefore, they should prioritise the digitalisation of the service for virtual assistants, augmented reality, Artificial intelligence, and virtual reality. Second, Wi-Fi in-flight can also reduce the delay in flight service. For example, offering an extra hour of Wi-Fi usage. Third, airline managers should consider the gate location. Some passengers are stressed and frustrated even before the flight departs, as some companies neglect to address these passengers' negative experiences. Fourth, companies should recover the delay difference and the consequences of passenger dissatisfaction by implementing automatic recovery strategies when a delay occurs. A limited voucher with a flight value can serve as a financial stimulus for the company's brand. This can turn a rage passenger into a loyal one.

This study suggests future research directions. First, the focus of the study can be expanded towards consumers from diverse cultural backgrounds, which would impact consumer satisfaction dimensions. Specifically, investigating cultural moderators and their role in affecting customer satisfaction could also be assessed. Given the rise of emergent technologies such as AI assistants and AI delay prediction, it would be interesting for researchers to examine their impact on consumer satisfaction. Third, because this study approach is more inductive, the theoretical base is integrated after reviewing consumer satisfaction from the datasets. Despite the challenge in finding many examples of real-world Big Data, this study can be replicated in different datasets, primarily if more information regarding context can be determined. This could lead to further theoretical development under new assumptions. A longitudinal study could help examine frequent delays in consumer behavioural outcomes apart from satisfaction, such as brand loyalty and repurchase intention. Additionally, analysing demographic and psychographic profiles could help analyse how flight delays affect consumer satisfaction.

ORCID

Olavo Pinto http://orcid.org/0000-0002-5038-4060
Amélia Brandão http://orcid.org/0000-0003-2751-7272
Mahesh Gadekar http://orcid.org/0000-0002-2229-069X

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