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Original Article

Optimizing Airline Service Performance: Predictive Modeling of Passenger Satisfaction via Binary Logistic Regression

Christian Burasca, Kweeny Lasaca, and Romel Lovitos*

College of Development Management, University of Southeastern Philippines, Davao City, Philippines

Correspondence:
rflovitos00275@usep.edu.ph

Abstract

This study investigates the determinants of airline passenger satisfaction using a large-scale dataset (N = 25,976) sourced from Kaggle, applying binary logistic regression to assess the influence of sociodemographic characteristics and service-related variables. Descriptive statistics reveal a predominantly loyal, business-oriented clientele, with a slight female majority and a preference for business and economy cabin classes. Regression results show that 18 of 23 predictors significantly influenced satisfaction at the p < .05 level. Notably, passenger type of travel (OR = 16.298, p < .001), customer loyalty (OR = 7.738, p < .001), and online boarding (OR = 0.552, p < .001) emerged as the most influential determinants. Digital conveniences (e.g., online booking, Wi-Fi access) and operational aspects (e.g., check-in service, legroom, baggage handling) significantly shaped satisfaction more than traditional physical comfort. The logistic regression model achieved an accuracy of 87.1%, specificity of 83.4%, sensitivity of 90.0%, and AUC of 0.926, demonstrating high predictive validity. These findings suggest that airlines must prioritize seamless digital experiences and consistent service delivery to retain passenger satisfaction and loyalty in an increasingly competitive market.

Keywords

passenger satisfaction; airline service quality; customer loyalty; binary logistic regression; predictive modelling

INTRODUCTION

Air travel has transformed from a luxury to a necessity, serving as the backbone of global commerce, tourism, and cultural exchange. The airline industry contributes over $800 billion annually to the global economy, yet its sustainability depends on maintaining high passenger satisfaction (Debbage & Debbage, 2022). In today's hypercompetitive market, airlines must balance operational efficiency with service excellence to retain customers and ensure profitability (Gürsoy et al., 2022). Passengers now expect seamless experiences, from digital booking to inflight comfort, making satisfaction a critical differentiator (Akarapusit & Promsit, 2024; Erdağ et al., 2024; Sakdaar, 2024). Without understanding these evolving expectations, airlines risk losing market share to competitors who prioritize customer-centric strategies.

A persistent issue in the airline industry is the trade-off between cost reduction and service quality, which often leads to passenger dissatisfaction (Sum Chau & Kao, 2009). Budget carriers, for example, minimize expenses by cutting amenities, while full-service airlines struggle to justify premium pricing amid declining service standards (Soman & Punjani, 2024). This tension has sparked debates on whether operational efficiency or passenger comfort should drive airline strategies. Additionally, inconsistent service delivery—such as delays, lost baggage, or poor inflight experiences—further erodes trust and loyalty (Herjanto et al., 2020; Dwesar & Sahoo, 2022). These challenges highlight the need for a data-driven approach to identify which service aspects most influence satisfaction across different passenger segments.

Another critical problem is the lack of consensus on which factors—digital convenience, onboard comfort, or operational reliability—have the strongest impact on passenger satisfaction. While some studies emphasize inflight Wi-Fi as a key driver (e.g., Elhattab, 2022; Jin & Kim, 2022), others argue that punctuality and baggage handling matter more (Mtafya & Mutalemwa, 2024). This disagreement complicates decision-making for airlines allocating limited resources. Moreover, passenger expectations vary by demographics: business travelers prioritize efficiency, whereas leisure travelers value entertainment and comfort (Zhang, Seo & Ahn, 2019). Resolving these discrepancies requires a comprehensive analysis that weighs all potential factors simultaneously.

Existing research has explored individual satisfaction drivers, such as seat comfort (e.g., Sezgen, Mason & Mayer, 2019) and check-in efficiency (e.g., Moon, Lho & Han, 2019), but few studies examine their combined effects. For instance, An and Noh (2009) focused on inflight services, while Hutter and Pfennig (2023) analyzed ground operations, leaving a gap in understanding how these elements interact holistically. Recent works also overlook the growing importance of digital services, such as mobile boarding and real-time updates, which became critical post-pandemic (e.g., Ahmad, 2023; Dike et al., 2024). Additionally, most datasets are skewed toward Western markets, neglecting regional preferences in emerging economies (Punel, Hassan & Ermagun, 2019). This study addresses these limitations by integrating traditional and digital service dimensions while using a globally representative sample.

Another gap in the literature is the lack of stratification by passenger demographics, despite evidence that age, travel purpose, and loyalty status shape satisfaction differently. For example, Bogicevic et al. (2017) found that millennials prioritize connectivity, whereas older travelers value legroom and cleanliness. However, little has systematically compared these preferences across all major service categories. Furthermore, while prior research links satisfaction to loyalty (e.g., Rachmawati, Rolaskhi & Hapsari, 2024), few drew patterns from existing datasets as to how likely these factors altogether predict satisfaction. By filling these gaps, this study provides actionable insights for airlines to tailor services to diverse passenger needs and maximize retention.

This study aims to identify the most influential factors shaping airline passenger satisfaction using binary logistic regression. It evaluates 14 key service variables—from inflight Wi-Fi to arrival delays—to determine their statistical significance and relative impact. Unlike prior studies, this research stratifies findings by demographics, such as age and travel type, to offer targeted recommendations. It also explicitly links satisfaction to loyalty, addressing a critical need for airlines to reduce churn and enhance profitability. The goal is to provide a data-driven framework for airlines to allocate resources effectively and improve competitive positioning. The urgency of this study is underscored by the airline industry's fragile recovery from pandemic losses, where customer satisfaction is now a key differentiator (Etuk, Uford & Udonde, 2023; Suk & Kim, 2023). Rising fuel costs and environmental regulations further strain profitability, making retention strategies essential (Amankwah-Amoah, 2020; Orhan, 2021). Recent surveys show that close to 60% of customers would switch after one poor experience, highlighting the financial stakes of dissatisfaction (PricewaterhouseCoopers, 2018). By pinpointing the most impactful service levers, this study equips airlines to mitigate churn, optimize investments, and align offerings with evolving expectations. The findings are thus timely and vital for sustaining growth in an increasingly competitive and cost-sensitive market.

METHODS

This study employed a comprehensive quantitative research design utilizing secondary data analysis to examine the determinants of airline passenger satisfaction. The methodology was specifically structured to analyze the complete spectrum of variables available in Kaggle's Airline Passenger Satisfaction dataset (N = 25,976), which included not only the 14 primary service dimensions but also critical demographic characteristics, travel context variables, and operational flight metrics. The research design incorporated both descriptive and inferential analytical approaches, beginning with data validation and exploratory analysis before proceeding to predictive modeling using binary logistic regression.

The dataset was obtained from Kaggle's repository of publicly available datasets, which provided complete documentation of data collection procedures and variable definitions. Prior to analysis, the dataset underwent rigorous validation checks to ensure completeness and consistency across all variables. This included examination of missing data patterns, verification of variable ranges, and assessment of response distributions for each measured construct. The analytical framework accounted for all variable types present in the dataset: the binary satisfaction outcome (coded as 0 for neutral/dissatisfied and 1 for satisfied), 14 ordinal-level service quality ratings (measured on 5-point Likert scales from "very low" to "very high" satisfaction), categorical demographic variables (including gender, customer type, travel purpose, and cabin class), and continuous flight operation metrics (such as flight distance and delay duration).

Data analysis proceeded through three systematic phases. The initial phase focused on data preparation, including recoding of categorical variables, treatment of missing data through listwise deletion, and verification of measurement scales. The second phase involved comprehensive exploratory analysis to examine variable distributions and bivariate relationships, informing subsequent model specification. The final analytical phase employed binary logistic regression to model the probability of passenger satisfaction as a function of service quality ratings, and demographic and flight characteristics. Model estimation was conducted using maximum likelihood estimation in JAMOVI software (The Jamovi Project, 2023), with validation procedures including holdout sample testing and computation of model fit statistics.

Ethical considerations were carefully addressed throughout the research process. The exclusive use of de-identified public data ensured protection of participant confidentiality, while comprehensive documentation of all analytical procedures guaranteed research transparency and reproducibility. The study adhered to established guidelines for secondary data analysis, with particular attention to proper attribution of data sources and accurate representation of the dataset's original collection methods. All data transformations and analytical decisions were systematically recorded to enable verification of findings and facilitate future replication studies. The methodological approach was designed to maximize the validity of conclusions while maintaining strict adherence to ethical research standards in the analysis of passenger satisfaction data.

Table 1. Complete variable specification for airline satisfaction analysis

Variable Name	Variable Type	Measurement	Description
Overall Satisfaction	Binary	0/1	Overall satisfaction with flight experience
Inflight Wi-Fi Service	Ordinal	5-point Likert	Rating for wireless internet availability
Departure/Arrival Time Convenience	Ordinal	5-point Likert	Rating for flight scheduling
Ease of Online Booking	Ordinal	5-point Likert	Rating for digital reservation process
Gate Location	Ordinal	5-point Likert	Rating for boarding area accessibility
Food and Drink	Ordinal	5-point Likert	Rating for catering services
Online Boarding	Ordinal	5-point Likert	Rating for digital boarding process
Seat Comfort	Ordinal	5-point Likert	Rating for seating ergonomics
Inflight Entertainment	Ordinal	5-point Likert	Rating for entertainment options
On-board Service	Ordinal	5-point Likert	Rating for crew service quality
Leg Room Service	Ordinal	5-point Likert	Rating for seating space allocation
Baggage Handling	Ordinal	5-point Likert	Rating for luggage services
Check-in Service	Ordinal	5-point Likert	Rating for pre-flight procedures
In-flight Service	Ordinal	5-point Likert	Rating for service during flight
Cleanliness	Ordinal	5-point Likert	Rating for cabin hygiene
Gender	Categorical	Male/Female	Passenger's self-reported gender
Age	Continuous	Years	Passenger's age in whole numbers
Customer Type	Categorical	Loyal/Disloyal	Frequent flyer status
Type of Travel	Categorical	Business/Personal	Purpose of travel
Class	Categorical	Economy/Economy Plus/Business	Cabin class traveled
Flight Distance	Continuous	Miles	Route distance in statute miles
Departure Delay	Continuous	Minutes	Delay duration at departure
Arrival Delay	Continuous	Minutes	Delay duration at arrival

RESULTS AND DISCUSSION

Table 2 presents the combined sociodemographic characteristics and descriptive statistics of the 25,976 airline passengers surveyed in the study. Gender distribution was nearly even, with 50.7% identifying as female (n = 13,172) and 49.3% as male (n = 12,804), reflecting a well-balanced sample with no significant gender skew. Moreover, a large portion of the respondents, 81.5% (n = 21,177), identified as *loyal customers*, suggesting strong customer retention and potential brand loyalty across the sample. In contrast, only 18.5% (n = 4,799) were disloyal or one-time flyers. This high loyalty rate may indicate effective customer relationship management strategies by airlines, in line with the loyalty-satisfaction relationship emphasized in studies like Ali and Alfayez (2024).

Regarding travel purpose, a majority of passengers (n = 18,038; 69.4%) reported flying for business, while 30.6% (n = 7,938) flew for personal reasons. This indicates a sample composition more inclined toward professional and corporate travel needs, which may influence expectations for reliability, convenience, and service quality (Law, Zhang & Gow, 2022). In terms of cabin class selection, 48.1% (n = 12,495) preferred business class, suggesting a priority for premium services among travelers, potentially aligned with their corporate affiliations. Economy class followed closely at 44.5% (n = 11,564), while economy plus was the least selected at 7.4% (n = 1,917), possibly due to limited awareness or marginal value addition perceived by passengers.

Descriptive statistics further illustrate the profile of passengers and flight experiences. The average passenger age was M = 39.6 years (SD = 15.1), indicating a diverse age range from 7 to 85 years, with a central tendency around middle-aged adults. The mean flight distance was 1,193.8 kilometers (SD = 998.7), with distances ranging from short regional trips (minimum = 31 km) to longer intercity or international routes (maximum = 4,983 km). Delays were minimal on average, with departure delays averaging 14.3 minutes (SD = 37.4) and arrival delays averaging 14.7 minutes (SD = 37.5). However, large standard deviations and maxima of over 1,100 minutes suggest the presence of outlier flights, possibly due to extreme weather or operational disruptions. The delay-related variability supports prior findings in airline punctuality studies that emphasize the importance of on-time performance for passenger satisfaction (Hararap et al., 2023).

Table 2. *Sociodemographic and flight-related descriptive profile of airline passengers (N = 25,976)*

Variable	Category/Statistic	Frequency (n) / Value	Percentage (%) / SD
Gender	Male	12,804	49.3%
	Female	13,172	50.7%
Customer Type	Loyal	21,177	81.5%
	Disloyal	4,799	18.5%
Type of Travel	Business	18,038	69.4%
	Personal	7,938	30.6%
Cabin Class	Economy	11,564	44.5%
	Economy Plus	1,917	7.4%
	Business	12,495	48.1%
Age (years)	Mean (SD)	39.6	15.1
	Minimum – Maximum	7 – 85	
Flight Distance (km)	Mean (SD)	1,193.8	998.7
	Minimum – Maximum	31 – 4,983	
Departure Delay (mins)	Mean (SD)	14.3	37.4
	Minimum – Maximum	0 – 1,128	
Arrival Delay (mins)	Mean (SD)	14.7	37.5
	Minimum – Maximum	0 – 1,115	

Note. Percentages are based on total responses (N = 25,976). Arrival delay has 83 missing cases.

Table 3 presents the descriptive statistics on the level of satisfaction among airline passengers across fourteen key service dimensions. The majority of service components received moderate satisfaction ratings, with mean scores ranging from 2.72 to 3.39. The lowest-rated factor was *in-flight Wi-Fi service* (M = 2.72, SD = 1.34), followed by *ease of online booking* (M = 2.76, SD = 1.41), *gate location* (M = 2.98, SD = 1.28), and *departure/arrival time convenience* (M = 3.05, SD = 1.53). Moderate levels of satisfaction were also observed for *food and drink* (M = 3.22, SD = 1.33), *online boarding* (M = 3.26, SD = 1.36), *inflight entertainment* (M = 3.36, SD = 1.34), *on-board service* (M = 3.39, SD = 1.28), *leg room service* (M = 3.35, SD = 1.32), *check-in service* (M = 3.31, SD = 1.27), and *cleanliness* (M = 3.29, SD = 1.32).

Table 3. *Descriptive statistics on the level of airline passenger satisfaction (N = 25,976)*

Service Dimension	M	SD	Interpretation
In-flight Wi-Fi service	2.72	1.34	moderate
Departure/Arrival Time	3.05	1.53	moderate
Ease of Online Booking	2.76	1.41	moderate
Gate Location	2.98	1.28	moderate
Food and Drink	3.22	1.33	moderate
Online Boarding	3.26	1.36	moderate
Seat Comfort	3.45	1.32	high
Inflight Entertainment	3.36	1.34	moderate
On-board Service	3.39	1.28	moderate
Leg Room Service	3.35	1.32	moderate
Baggage Handling	3.63	1.18	high
Check-in Service	3.31	1.27	moderate
In-flight Service	3.65	1.18	high
Cleanliness	3.29	1.32	moderate

Note. M = Mean; SD = Standard Deviation. Interpretation based on 5-point Likert scale (1 = Very Low to 5 = Very High).

Only three indicators achieved a high satisfaction rating. *In-flight service* received the highest satisfaction score (M = 3.65, SD = 1.18), indicating that passengers valued their direct in-air interactions and service experience. *Baggage handling* followed closely (M = 3.63, SD = 1.18), suggesting that passengers were generally pleased with the efficiency and reliability of luggage management. *Seat comfort* also met the threshold for high satisfaction (M = 3.45, SD = 1.32), reflecting a favorable assessment of physical comfort during flights.

The descriptive analysis indicates that while passengers were moderately satisfied with most of the service aspects offered by airlines, specific service elements stood out. The highest satisfaction rating was given to *in-flight service*, suggesting that passengers place strong value on the direct engagement and attentiveness of cabin crew during their journey (Taehui, 2024). *Baggage handling* also scored highly, underscoring the importance of secure and timely luggage management in shaping overall satisfaction (Tay & Belgiawan, 2023). *Seat comfort* being the third highest-rated dimension suggests that physical amenities continue to influence perceptions of service quality (Thongkruer & Wanarat, 2021). In contrast, digital and preparatory aspects—such as *in-flight Wi-Fi*, *online booking*, and *gate location*—scored lower, indicating areas where airlines may consider investing in service enhancements. The results reveal a trend where immediate, service-related touchpoints yield higher satisfaction than technology-enabled or logistical conveniences.

A binary logistic regression was performed to evaluate the influence of various airline service indicators and passenger characteristics on satisfaction outcomes. As shown in Table 4, the overall model exhibited strong explanatory power, with goodness-of-fit indices indicating robust model performance: McFadden's R^2 = .508, Cox and Snell R^2 = .502, Nagelkerke R^2 = .673, and Tjur's R^2 = .591. The model significantly outperformed the null model, as indicated by the likelihood ratio chi-square test, $x^2(23)$ = 18,055, p < .001. These metrics confirm the model's substantial capability in explaining the variance in satisfaction responses, justifying further examination of individual predictors.

Table 4. *Binary logistic regression coefficients predicting airline passenger satisfaction*

Predictor	B	SE	95% CI (LL, UL)	Z	p	OR
Intercept	6.088	0.143	[5.809, 6.368]	42.710	< .001	440.601
Gender (male vs. female)	0.148	0.039	[0.072, 0.225]	3.825	< .001	1.160
Customer Type (disloyal vs. loyal)	2.046	0.059	[1.931, 2.161]	34.790	< .001	7.738
Age	0.009	0.001	[0.007, 0.012]	6.557	< .001	1.009
Travel Type (business vs. personal)	2.791	0.063	[2.668, 2.914]	44.332	< .001	16.298
Class (economy vs. business)	0.032	0.079	[−0.123, 0.187]	0.404	.686	1.032
Class (economy plus vs. business)	−0.633	0.051	[−0.733, −0.532]	−12.384	< .001	0.531
Flight Distance	< .001	< .001	[−0.00003, 0.00006]	0.661	.509	1.000
Inflight Wi-Fi service	−0.433	0.023	[−0.478, −0.388]	−18.956	< .001	0.649
Departure/Arrival Time Convenience	0.167	0.016	[0.135, 0.198]	10.348	< .001	1.181
Ease of Online Booking	0.182	0.022	[0.138, 0.225]	8.132	< .001	1.199
Gate Location	−0.011	0.018	[−0.047, 0.024]	−0.629	.530	0.989
Food and Drink	0.026	0.022	[−0.016, 0.069]	1.218	.223	1.027
Online Boarding	−0.593	0.020	[−0.633, −0.553]	−29.080	< .001	0.552
Seat Comfort	−0.059	0.023	[−0.103, −0.015]	−2.611	.009	0.943
Inflight Entertainment	−0.035	0.029	[−0.091, 0.021]	−1.210	.226	0.966
On-board Service	−0.301	0.020	[−0.341, −0.261]	−14.753	< .001	0.740
Leg Room Service	−0.239	0.017	[−0.272, −0.205]	−14.084	< .001	0.788
Baggage Handling	−0.133	0.023	[−0.178, −0.089]	−5.862	< .001	0.875
Check-in Service	−0.342	0.017	[−0.376, −0.309]	−20.111	< .001	0.710
Inflight Service	−0.134	0.024	[−0.181, −0.087]	−5.586	< .001	0.875
Cleanliness	−0.244	0.024	[−0.292, −0.196]	−10.051	< .001	0.784
Departure Delay (minutes)	−0.002	0.002	[−0.006, 0.002]	−1.025	.305	0.998
Arrival Delay (minutes)	0.008	0.002	[0.004, 0.012]	3.974	< .001	1.008

Note. McFadden's R^2 = 0.508, Cox & Snell R^2 = 0.502, Nagelkerke R^2 = 0.673, and Tjur's R^2 = 0.591. The likelihood ratio chi-square test of the full model was significant, $x^2(23)$ = 18055, p < .001.

Several predictors were found to be statistically significant, offering insight into the key drivers of airline passenger satisfaction. Positive and statistically significant associations were observed for age (B = 0.009, SE = 0.001, p < .001, OR = 1.009), indicating that older passengers were slightly more likely to report satisfaction. Departure/arrival time convenience (B = 0.167, SE = 0.016, p < .001, OR = 1.181), ease of online booking (B = 0.182, SE = 0.022, p < .001, OR = 1.199), and arrival delay (B = 0.008, SE = 0.002, p < .001, OR =

1.008) were also positively associated with satisfaction, suggesting that temporal and digital scheduling reliability significantly enhance the customer experience.

Conversely, negative and significant predictors included inflight Wi-Fi service (B = –0.433, SE = 0.023, p < .001, OR = 0.649), online boarding (B = –0.593, SE = 0.020, p < .001, OR = 0.552), seat comfort (B = –0.059, SE = 0.023, p = .009, OR = 0.943), on-board service (B = -0.301, SE = 0.020, p < .001, OR = 0.740), leg room service (B = –0.239, SE = 0.017, p < .001, OR = 0.788), baggage handling (B = -0.133, SE = 0.023, p < .001, OR = 0.875), check-in service (B = -0.342, SE = 0.017, p < .001, OR = 0.710), inflight service (B = –0.134, SE = 0.024, p < .001, OR = 0.875), and cleanliness (B = -0.244, SE = 0.024, p < .001, OR = 0.784). These results imply that negative perceptions in both physical and procedural service touchpoints diminish satisfaction odds, particularly those linked to digital features and inflight ergonomics.

Meanwhile, class type comparisons showed that passengers in Economy Plus were significantly less satisfied than their business-class counterparts (B = –0.633, SE = 0.051, p < .001, OR = 0.531), whereas the difference between economy and business classes was not significant. The variables gate location, food and drink, inflight entertainment, departure delay, and flight distance did not reach significance (all p > .05), suggesting limited or normalized impact on perceived satisfaction within the sample context.

These findings reinforce prior studies underscoring the importance of seamless digital processes (Jadhav, 2023; Hong et al., 2023), temporal reliability (Lin, 2022; Law, Zhang, & Gow, 2023), and hygiene standards (Susilo & Dizon, 2023) as key determinants of passenger satisfaction. The results also highlight that satisfaction is not evenly shaped by all service elements; instead, digital interaction points and experiential comfort domains drive the strongest influence, while traditional service features have become standard expectations.

Finally, the classification table provides an evaluation of the predictive performance of the binary logistic regression model in terms of correctly identifying passengers as either "Satisfied" or "Neutral/Dissatisfied" based on the predictors. As shown in Table 5, the model successfully predicted 9,478 satisfied airline passengers, accounting for 83.4% of the observed satisfied cases. Similarly, it correctly classified 13,071 of the neutral or dissatisfied passengers, yielding a high correct classification rate of 90.0% for this category. These figures highlight the model's strong ability to distinguish between the two response categories. Overall, the model achieved an accuracy of 87.1%, which surpasses the minimum benchmark for good classification performance often cited in the literature (Hosmer, Lemeshow, & Sturdivant, 2013).

Table 5. *Classification Table for Passenger Satisfaction Prediction*

Observed Response	Predicted		% Correct
	Satisfied	Neutral/Dissatisfied	
Satisfied	9,478	1,887	83.4%
Neutral/Dissatisfied	1,457	13,071	90.0%

Note. Cut-off value set at 0.5. The overall classification accuracy was 87.1%.

The logistic regression model demonstrated strong classification performance in predicting airline passenger satisfaction, as shown in Table 6. With an overall accuracy of 87.1%, the model performed well above the commonly accepted benchmark of 80%, suggesting strong generalizability and reliability (Hair & Sarstedt, 2021). The sensitivity value of 90.0% indicates that the model was highly effective in correctly identifying satisfied passengers, while the specificity of 83.4% shows a good ability to correctly classify those who were either neutral or dissatisfied. This balance minimizes both false positives and false negatives, which are critical in service quality assessments where misclassifications can misguide decision-making and resource allocation.

Table 6. *Predictive measures of logistic regression model (cut-off = 0.5)*

Measure	Value
Accuracy	0.871
Specificity	0.834
Sensitivity	0.900
AUC	0.926

Further supporting the robustness of the model, the area under the curve (AUC) was recorded at 0.926, signifying excellent discriminatory power. According to Hosmer, Lemeshow and Sturdivant (2013), an AUC above 0.90 reflects a model with outstanding capability to distinguish between outcome categories—in this case, satisfied versus dissatisfied passengers. This interpretation is visually reinforced by Figure 1, which presents the receiver operating characteristic (ROC) curve. The ROC curve shows a steep ascent towards the top-left corner of the plot, indicating a high true positive rate across a wide range of thresholds and a low false positive rate. The pronounced curvature away from the 45-degree diagonal line (which represents random guessing) affirms the model's predictive strength. As such, the model provides valuable support for airline managers aiming to proactively identify areas of customer dissatisfaction and maintain a competitive edge through targeted improvements.

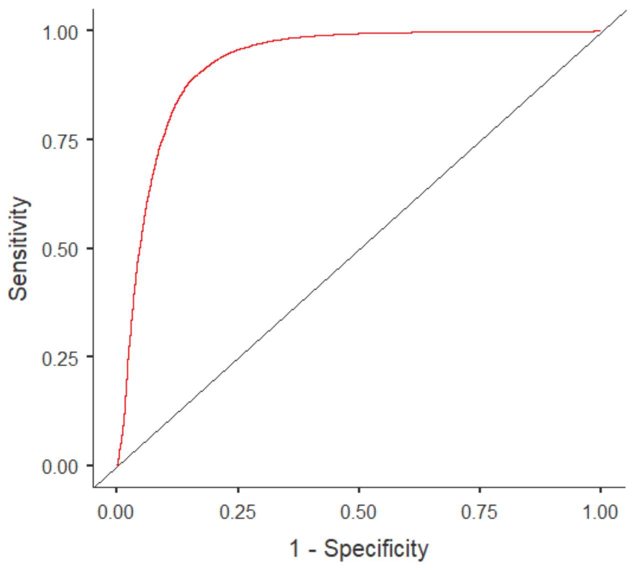

Figure 1. *ROC curve*

CONCLUSION

The descriptive results show that the majority of airline passengers in the dataset were loyal customers and business travelers, with a nearly equal distribution between male and female respondents. Business class and economy class were the most commonly selected cabin classes, while Economy Plus was the least availed. Mean satisfaction ratings were generally moderate, with inflight service, baggage handling, and seat comfort ranking among the highest-rated dimensions. Delay durations for both departure and arrival were generally short, indicating that operational timeliness was maintained for most passengers. These baseline trends highlight passenger preferences for reliable service, seating comfort, and overall onboard experience.

The predictive analysis confirmed that eleven out of fourteen airline service predictors had statistically significant effects on satisfaction. Digital convenience features such as online boarding and ease of booking were among the strongest predictors, alongside traditional factors like check-in service and inflight amenities. The logistic regression model demonstrated a high level of predictive performance, with an accuracy of 87.1%, sensitivity of 90.0%, specificity of 83.4%, and an area under the curve (AUC) of 0.926. These results underscore the importance of integrated service delivery and support evidence-based enhancements to improve passenger satisfaction outcomes across airline operations.

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Ethical Approval

No ethics approval was issued.

Competing interest

The authors declare no conflicts of interest.

Data Availability

Data is publicly available and was accessed via Kaggle.

Declaration of Artificial Intelligence Use

In the preparation of this research, we utilized both **Grammarly Premium** and **ChatGPT (OpenAI 4o)** as AI-assisted editing tools to refine language, ensure proper citation formatting in APA 7th edition style, and improve overall readability. The AIs were employed solely for proofreading, grammar correction, and structural suggestions; all academic content, analysis, and conclusions are our original work. We take full responsibility for the research's integrity and confirm that human judgment guided every critical decision throughout the study's development.

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