Decoding User Reviews for Low-Cost Airlines Marketing: A Global Analysis of Passenger Preferences

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Article Info

Abstract

The airline industry is a key component in the transportation and tourism sectors thanks to its economic potential and global scope, and the complex structure of customer preferences, competitive environment, and changing dynamics require examination of the marketplace. In this context, it has been determined that many studies have focused on user studies in the airline market, while only a few studies have examined the Low-cost airline sub-context in the airline market. This study aims to investigate the factors affecting consumer recommendation and rating scores through user reviews in the context of Low-cost airlines. In the study, regression analyzes and difference tests were used on 5672 user reviews on airlinequality.com about 20 airline brands on Skytrax's World's Best Low-cost Airlines 2023 list. In the regression analysis, it was seen that value for money was the most important determining factor in recommendation status and rating scoring, followed by ground service, cabin crew service, seat comfort and food and beverage variables. Difference tests reveal that solo leisure travelers tend to rate and recommend higher. It is also concluded that first-class passengers using LCC airlines have higher tendency for rating scores higher and recommending.

1. Introduction

In the Web 2.0 era (O'reilly, 2009) and beyond, web users began communicating with each other in two-way ways and began to influence other users by sharing their opinions. In previous years, marketing communication in the form of messages conveyed by companies to consumers as "announcements" has now become a form in which consumers interact with both the company and other consumers. Today's internet users spend an average of 6 hours 37 minutes of their day on the internet (We Are Social & Meltwater, 2023). In parallel with the increase in the time users spend on the internet, the variety and intensity of the content they share with other users have increased in recent years. Today's consumer uses the web for a broad range of different purposes, such as finding information, staying in touch with friends and family, keeping up to date with news and events (We Are Social & Meltwater, 2023). They also consume the content, participate in discussions, share information, and affect others' actions (Heinonen, 2011). These developments require understanding the type and content of consumers' online communications with each other and with brands.

As consumers' interaction with brands and other consumers increases, the reviews written by consumers on digital platforms have become important. Through these reviews, consumers can share their positive/negative opinions and experiences about products and services with thousands of

users. On the consumer side, online reviews help consumers obtain product information and alleviate uncertainties before the purchase decision (Yan et al., 2015). For the company side, online reviews can help understand the customer and the market in several industries, such as movies (Duan et al., 2008), retail (Floyd et al., 2014), healthcare (Abirami & Askarunisa, 2017), cosmetics (Haddara et al., 2020). Tourism is one of the industries highly affected by the COVID-19 pandemic, as international tourist arrivals dropped to 406 million people in 2020 worldwide. However, the effect of COVID-19 disappeared over time as the increase to 1.286 billion people (33.9% increase between 2022 and 2023) took place (UNWTO, 2023). Within the landscape of online review analysis, the tourism sector presents a critical potential due to its experiential characteristics and the ability of consumers to influence each other.

The airline industry is one of the significant areas where competition is intense with different customer segments and product/service groups within the scope of tourism (Aydın, 2024; Duran et al., 2024). Different types of airline business models, such as full-service and Low-cost airlines, have emerged to meet the needs of different customer groups in the airline market. Low-cost airline companies "*offer lower fares to attract passengers by reducing their service costs by means such as reducing free in-flight services, standardizing airplane fleet and cabins, increasing luggage restrictions, and using secondary airports*" (Chang & Hung, 2003). IATA (2022)

report indicates that even though LCC companies carry more passengers than network carriers in the intra-European market, network carriers have increased market share by 9% with the help of higher maintained service levels. Thus, service levels and market perception of these levels are essential tasks for LCC marketing decision-makers.

The primary rationale for the study is to provide the information necessary to develop more effective strategies to increase user experience and satisfaction in the airline industry. This study conducts a multidimensional analysis by examining the factors affecting the effectiveness of user recommendations and the impact of these factors on rating scores using online data. In this way, it provides a better understanding of the main motivations that shape users' evaluations and adopts a more comprehensive analysis approach by combining big data (online user reviews) and quantitative data (consumer surveys). In addition, the study focuses on the low-cost airlines (LCC) sector, in particular, by conducting a more in-depth examination of this sector's unique dynamics and user expectations. This reveals its originality by offering more specific recommendations for the individual needs of the LCC sector. The study uses a current dataset (Skytrax World's Best Low-Cost Airlines 2023 list) to reflect the sector's most current trends and user expectations. Analyzing this list can guide current sector dynamics in the airline sector. For these reasons, the study reveals its originality in contributing to the airline literature and leading marketers in the airline sector.

This study set out to examine LCC passengers in an online review context to identify the specific points of user recommendations through a variety of determinants. The first research question focuses on the factors regarding the user recommendation activity in the online review, while the latter one examines the rating score with determinants. Dalla Valle and Kenett (2018) highlight the value of integrating big data and customer surveys for better understanding in their study. This study follows that approach and chooses the top Low-cost airline companies in Skytrax World's Best Low-cost Airlines 2023 list (Skytrax, 2023), including the brands selected through customer surveys, and integrates the online review data (Skytrax user reviews on airlinequality.com) as the sample for the study. Employing a dataset obtained for the LCC airline companies with a regression analysis helps to explore the user motivations in the airline industry for the specific context.

2. Theoretical Framework

In the conceptual framework of the study; information about electronic word of mouth and user comments, eWOM in the airline market is given.

2.1. Electronic word of mouth and user reviews

Consumers live in communities and societies and affect each other through communication and activities. This phenomenon leads to word of mouth (WOM) being a fundamental concept in consumer research. According to Westbrook (1987), WOM refers to the informal communication activity between consumers on the topics of ownership, usage, and characteristics of specific products/services and their sellers. With the emergence of increasing technology and digital platforms in recent decades, the concept of WOM has also been shaped and evolved into a new dimension in the form of electronic word of mouth

(eWOM). Defined as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet" by Hennig-Thurau, Gwinner, Walsh & Gremler (2004), e-WOM is a determinant factor for the consumer decision-making in the online context. Consumers, who were previously able to communicate with relatively limited circles in the WOM era, can now influence thousands of people over the web with the help of the internet and social media channels in the eWOM era. In this regard, marketing decision-makers focus on eWOM to better understand consumer behavior and the market.

The multifaceted nature of the eWOM concept includes several aspects for business decision-makers. The first aspect refers to justifications for producing content for eWOM. Web users generate content for eWOM for a wide range of reasons, including reputation, sense of belonging, and enjoyment of helping other consumers (Cheung & Lee, 2012). The second aspect is about the rationality of trusting in communications. Relying on WOM communication contains a basic idea, as people have more credible perceptions about them and evaluate WOM communication as "people like me" (Allsop et al., 2007). The third aspect represents the conceptual structures associated with the eWOM concept. According to Cheung and Thadani (2012), the eWOM concept is related to stimuli-related factors (argument quality, valence and so forth), receivers-related factors (involvement, prior knowledge), communicators-related factors (expertise, trustworthiness, attribution), contextual factor (platform) and responses (eWOM adoption, purchase intention and so forth). Understanding the basic ideas and broad scope of eWOM is an essential start to marketing decision-making.

The effect of eWOM on business operations includes several consequences for marketing decision-makers. The first reality refers to consumers' expressions and the effect on the purchases, as the consumers' expression of satisfaction/dissatisfaction through product review pages can be an indicator of information for others and can influence the purchase decisions of potential customers (Liu et al., 2023; Wang et al., 2023a). This reality is reflected in the product/service sales amount. As another consequence, online reviews are found to be an indicator of product/service levels (Zhu & Zhang, 2010; Cui et al., 2012; De Maeyer, 2012). The cycle between satisfaction/dissatisfaction and sales amount and indication of product/service level refer to a basic level idea for brand managers. However, the facets of the content and the long-term effects of brand-related factors have crucial effects on decision-makers, leading to the necessity of updating brands' marketing strategies to more comprehensive levels on these perspectives (Oh & Park, 2020; Wang & Chan-Olmsted, 2020).

Tourism and hospitality are among the most critical industries in which the eWOM concept is highly effective. As consumer evaluations and sales volumes are critical in the industry, user reviews are used to understand the marketplace from customers' perspectives. Several studies (Sotiriadis & Van Zyl, 2013; Harris & Prideaux, 2017; Kanje et al., 2020; Filieri et al., 2021) examine the eWOM concept and various sub-contexts within the industry promise the new research avenues. The subsequent section focuses on the eWOM concept in the airline industry, where consumer preferences are highly affected by individual choices and are open to other users' ideas expressed in offline or online channels.

2.2. eWOM in airline market

While the airline industry presents similarities to other tourism contexts in terms of consumer preferences being influenced by individual experiences and other users' reviews, still has unique characteristics. According to Leong et al. (2015), airline companies need to provide reliable products and services to customers; as the airline industry includes intense competition, they could have significant problems unless they fulfill this side. The crucial part of staying competitive in the airline industry is identification of the choice criteria of customers formulating marketing segmentation and promotional strategies using that information (Chen & Chao, 2015). For the customer side, staying competitive is related to customer satisfaction. According to Park, Robertson & Wu (2004), the level of passenger satisfaction and value perception are related to meeting the customers' expectations. From this point of view, airline companies need to evaluate user-generated eWOM content on the web to better understand customer expectations and integrate this perspective into marketing decision-making.

The significant potential of user reviews highlights the importance of harnessing user reviews for decision-making. Lee & Yu (2018) indicate that online reviews can serve as a reliable substitute for airport service quality ratings and can also be used for validating the results of conventional industry standard survey results. Processing user reviews represents a different approach than collecting data from users through surveys and using tools such as SERVQUAL in previous years. Li, Mao, Wang & Ma (2022) call the approach as "crowdsourcing" and conclude the possibility of obtaining the thoughts/concerns from large group of passengers which leads to better problem-solving and identification of improvement areas. Considering the volume and complexity of user reviews, a comprehensive analysis is imperative to comprehend the diverse range of topics included within the discourse.

For a comprehensive analysis of the discourse, user reviews on digital platforms need to be transformed into meaningful results for marketing decision-making. In the first approach, classical correlation and regression models can be followed since review data in Skytrax (airlinequality.com), like websites, include numerical values. For example, Wang, Zheng, Tang, & Luo (2023b) employ the sentiment analysis and use the extracted emotions to study for the recommendation intention variable in Skytrax reviews. In the second approach, a decoding process takes place. Several methodologies such as sentiment analysis (Song et al., 2020), latent semantic analysis (Sezgen et al., 2019), and topic modeling (Kwon et al., 2021; Farzadnia & Vanani, 2022) are used in previous researches to decode the passenger/market preferences from raw data. Approaches can employ different levels for data decoding. Using the macro-level approach, Punel, Hassan & Ermagun (2019) use online reviews to evaluate the differences among passengers from different geographical regions. On the other hand, using the micro-level approach, Bogicevic, Yang, Bilgihan & Bujisic (2013) employ the travelers' comments in their study and reveal satisficers-cleanliness and pleasant environment to spend time in - and dissatisfiers-security-check, confusing signage, and poor dining offer-in their study.

Examining the effects of airline passenger types, travel types, and cultures is essential for airline marketing. Sezgen, Mason & Mayer (2019) conclude that drivers of passenger satisfaction have differences regarding the air travel class (Low-cost or full-service carrier) in their study. In another study, Lim & Lee (2020) examine the service quality perceptions of full-service carrier and Low-cost carrier passengers and conclude reasonable differences. The authors assess the topics and deduce that tangible dimension is the most significant dimension for full-service carrier customers, while reliability dimension is the significant dimension for Low-cost carrier customers. The characteristics of different types of airline customers can reflect different outcomes or emphasize different preferences in the airline industry. This study focuses on Low-cost carrier airline companies in specific, to examine users' recommendations with the determinant factors.

3. Methodology

3.1. Data collection

Tourism users on web share their experiences with other users through several channels such as Tripadvisor, Booking.com, Skytrax, while they target specific audiences in the marketplace. Skytrax (https://skytraxratings.com/) (Skytrax, 2024) is one of the specific website for the airline industry containing the user reviews regarding the flight experiences. This study uses airlinequality.com data for user reviews regarding airline industry. World's Best Low-cost Airlines 2023 list (Skyrtax, 2023) is employed for the sampling decision regarding companies and 20 airline companies are selected for the study sample. The company names are listed as AirAsia, Scoot, IndiGo, Flynas, Volotea, Transavia France, Sun Country Airlines, Southwest Airlines, airBaltic, Jet2.com, EasyJet, Vueling Airlines, Ryanair, Jetstar Airways, flyDubai, Peach, JetSMART Airlines, Jetstar Asia, Eurowings, SKY Airline.

Within the scope of the data collection, 12,939 passenger reviews and rating information were obtained from the Skytrax user reviews website (https://www.airlinequality.com). Data collection took place on 10 October 2023 and the Python programming language (Rossum, 1995) is employed for retrieving the review data and the range of reviews is between April 2015 and September 2023. 8.515 user reviews in the initial dataset were removed due to some missing user ratings. 5.672 user reviews are used as the sample of the study. SPSS package software is used for analysis (Verma, 2012).

3.2. Study sample

The variables regarding the review unit in the dataset includes seat comfort, cabin staff service, food & beverages, inflight entertainment, ground service, wifi & connectivity, value for money, recommended status and overall rating. Recommended status and overall rating are used as dependent (shown as green color in Figure 1), the former variables are used as independent variables (shown as yellow color in Figure 1). The variables in the dataset also contains traveler type and seat type information (shown as blue color in Figure 1) which are used for difference tests.
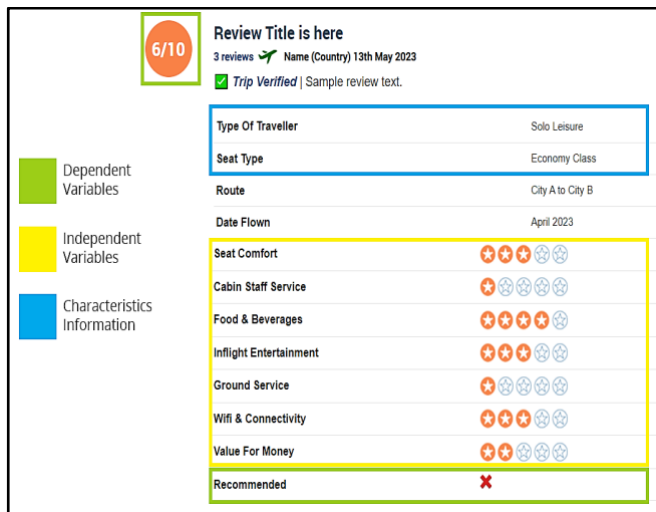
Figure 1. Online review sample for hypothesis testing
Source: Created by the authors.

Perceived value is an assessment made by a consumer regarding how much benefit they receive in return for a product or service. This assessment is related to the emotional, social and psychological benefits of the product as well as its physical properties. Therefore, the hypotheses addressing the perceived value of consumers are stated below (Zauner, Koller & Hatak, 2015).

H_1: The users' rating scores regarding seat comfort, cabin staff service, food & beverages, inflight entertainment, wifi & connectivity, ground service and value for money affect recommend status of the user.

H_2: The users' rating scores regarding seat comfort, cabin staff service, food & beverages, inflight entertainment, wifi & connectivity, ground service and value for money affect users' rating scores.

The hypotheses developed below are based on the expectancy-evaluation theory of attitude, which argues that a consumer's attitude toward a service is based on his or her expectations or beliefs about the service's relationship to other services (Alexander, 1976).

H_3: There are statistically significant differences in rating scores between traveler types.

H_4: There are statistically significant differences in rating scores between seat types.

The hypotheses generated according to social identity theory, which is presented to explain intergroup behavior and intergroup communication based on the intrinsic value that consumers place on their social group memberships and their desire to see certain social groups in a positive light, are presented below (Harwood, 2020).

H_5: There are statistically significant differences in recommendation statuses between traveler types.

H_6: There are statistically significant differences in recommendation statuses between seat types.

3.3. Descriptive stats

Independent variables are scored by star ratings and can have values between 1-5 in the user reviews. The descriptive stats of independent variables are presented in Table 1 which indicates the average values for all independent variables between 2.25 and 2.84. The average values for these variables are consistent to LCC airlines context of this study.

Table 1. Independent variable descriptive stats

Variables	Minimum	Maximum	Mean	Std. Deviation
Seat Comfort	1	5	2.46	1.377
Cabin Staff Service	1	5	2.84	1.569
Food & Beverages	1	5	2.32	1.390
Inflight Entertainment	1	5	2.25	1.253
WiFi & Connectivity	1	5	2.36	1.234
Ground Service	1	5	2.45	1.565
Value for Money	1	5	2.63	1.616

Characteristics information about users are presented in Table 2. According to table, 32.7% of users have solo leisure type, 31% of them have couple leisure, 23.8% of them have family leisure, and only 12.5% of them have business travel type. Travel class ratios is consistent with LCC airline context, as economy class has the majority (93.4%) travel classes of users.

Table 2. User characteristics descriptive stats

Variables	Subgroups	Frequency	Percentage (%)
Travel Type	Solo Leisure	1854	32.7
	Couple Leisure	1758	31.0
	Family Leisure	1352	23.8
	Business	708	12.5
Travel Class	First Class	13	0.2
	Economy Class	5296	93.4
	Business Class	182	3.2
	Premium Economy	181	3.2
	Total	5672	100

4. Result

4.1. Logistic regression analysis for recommendation status

Logistic regression is a statistical model that estimates the probability of an event occurring. In this model, the probability of an event occurring is examined when the dependent variables are binary or categorical (Hosmer & Lemeshow, 2000). In this context, in the research recommendation status is included in user reviews in two states (Yes and No); logistic regression methodology is employed in the first part of the analysis, consistent to the binary nature of dependent variable. The dependent variable for logistic regression analysis is recommendation status; while the independent variables are: seat comfort, cabin staff service, food & beverages, inflight entertainment, wifi & connectivity, ground service and value for money. Wald, Omnibus and Hosmer-Lemeshow tests and correct classification rates are mostly used to examine the goodness of fit of the binary logistic regression model in the research (Oktay & Orçanlı, 2014).

Below is the table showing that the model is statistically significant (p < 0.01) according to the Omnibus model.

Table 3. Omnibus tests of model coefficients

	Chi-square	df	Sig.
Step	5777.515	7	.000
Block	5777.515	7	.000
Model	5777.515	7	.000

The goodness of fit results are given in the table below and the reference category is shown as the "do not recommend" category.

Table 4. Determination of reference category

Original Value	Original Value
I recommend	1
I no not recommend	0

The Cox & Snell R^2 value, which shows the rate at which the independent variables explain the variance in the dependent variable in the model, and the Nagelkerke R^2 value, which is a relationship test measurement method developed to ensure that the Cox and Snell R^2 statistics take values in the range of 0-1 (Kalaycı, 2010), are presented in the table below.

Table 5. R^2 values of the model

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	1644.109[a]	.639	.875

Table 6. Correct classification ratio table of recommendation model

		Predicted		
		Recommended		Percentage Correct
Observed		Yes	No	
	No	1890	160	92.2
Recommended	Yes	138	3484	96.2
				94.7

The classification table is used to evaluate the goodness of fit of the model and the other method used to test the significance of the model is the Hosmer-Lemeshow test. The Hosmer-Lemeshow test statistic, an important measurement method used to test the logistic regression model, tests whether all logit coefficients outside the constant term are equal to zero. Indicated as "H_0" hypothesis, $\chi2$ values of the Hosmer-Lemeshow test statistics are calculated and included in Table 7. The hypotheses for this test are;

H_0: The parameters exhibit discrimination in terms of predictive power.

H_1: The parameters do not exhibit discrimination in terms of predictive power.

According to Table 5, the Cox & Snell R^2 value for the model is 0.639, which means that the independent variables explain 65.9% of the variance in the dependent variable. The Nagelkerke R^2 value for the model is 0.875, which means that the dependent variables explain 87.5% of the variance in the dependent variable.

Table 6 shows the prediction accuracies for the analysis and indicates that prediction accuracy regarding "Not recommended" status is 92.2, while for "recommended" status is 96.2 and for the whole model prediction accuracy is 94.7.

Table 7. Hosmer and lemeshow test

Chi-square	df	Sig.
17.942	8	.122

Table 7 indicates that the model is adequate model with a good fit (Chi-square: 17.942, df: 8 and p > 0.05) and H_0 hypothesis is supported which means that the parameters exhibit discrimination in terms of predictive power.

The observed and expected frequencies needed to calculate the Hosmer-Lemeshow test statistics and the Hosmer-Lemeshow test are included in Table 8. The data in dependent variable (recommendation status) is divided into ten groups and it is concluded that the observed and expected values are close to each other, which represents the model fit indicator.

Table 8. Contingency table for Hosmer and Lemeshow test

		Observed	Expected	Observed	Expected	Total
Step 1	1	663	665.389	3	0.611	666
	2	563	565.236	3	0.764	566
	3	565	565.062	2	1.938	567
	4	565	562.736	3	5.264	568
	5	554	550.340	13	16.660	567
	6	483	483.453	84	83.547	567
	7	193	195.749	375	372.251	568
	8	30	27.947	537	539.053	567
	9	5	4.981	563	563.019	568
	10	1	1.107	467	466.893	468

Table 9 includes the information of expected coefficient (β), standard error of expected coefficient (SEβ), Wald values, 95% confidence limits and significance values (Sig.) for the expected odds ratio. Examination of Wald values shows that seat comfort, cabin staff services, food & beverages, ground service, value for money variables have higher values than 2.

Table 9. Binary logistic regression analysis results

	β	Std. Error (β)	Wald	df	Sig	Exp (β)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Constant	-	-	-			-		
Seat Comfort	0.427	0.066	42.214	1	0.000	1.533	1.348	1.348
Cabin Staff Service	0.526	0.061	75.051	1	0.000	1.693	1.503	1.503
Food & Beverages	0.257	0068	14.440	1	0.000	1.293	1.133	1.133
Inflight Entertainment	0.085	0.065	1.707	1	0.191	1.088	0.958	0.958
Wifi	0.063	0.065	0.940	1	0.332	1.065	0.938	0.938
Ground Service	0.662	0.053	157.181	1	0.000	1.938	1.748	1.748
Value for Money	1.355	0.064	441.683	1	0.000	3.875	3.415	3.415

It is concluded that the seat comfort of airline passengers (β:0.427, p<0.05) significantly affects the passengers' recommendation for airline travel. The positive *β* value indicates that seat comfort increases passengers' likelihood of recommending activity. Passengers who recommend air travel are 15.33% more likely to perceive seating comfort than passengers who do not recommend air travel. The second finding of the table shows that cabin staff service has a significant and positive effect on passengers' recommendation of the airline (β:0.526, p<0.05). According to this result, passengers who recommend air travel are 16.93% more likely to perceive cabin staff service than passengers who do not recommend air travel. The third finding of the table indicates that the food & beverages (β:0.257, p<0.05) significantly affect the airline's recommendation. A positive β value indicates that the food & beverages variable increases the likelihood of a passenger's recommendation. According to this result, the passengers who recommend air travel are 12.93% more likely to perceive food quality than passengers who do not recommend air travel. The fourth finding states ground service significantly and positively affects passengers' recommendations (β:0.662, p<0.05). A positive β value means that ground service increases the likelihood of a passenger's recommendation. Passengers who recommend air travel have a positive effect on ground service. The probability of perception of service is 19.38% higher than that of passengers

who do not recommend air travel. The last finding of the table indicates that value for money has a significant and positive effect on passengers' recommendation (β:1.355, p<0.05). According to this result, the probability of perception of value for money for passengers who recommend is 38.75% higher than that of passengers who do not recommend.

4.2. Multiple Regression Analysis for Rating Score

Second hypothesis testing employs multiple regression analysis in the second stage of methodology. Multiple regression analysis measures the effect of more than one independent variable on a dependent variable. The dependent variable in the study refers to rating scores (1 to 10) and independent variables refer to seat comfort, cabin staff service, food & beverages, inflight entertainment, wifi & connectivity, ground service and value for money variables.

Since multiple regression analysis required normality, skewness and kurtosis values are examined in Table 10. Some researchers assume that the data have a normal distribution when the value obtained by dividing the skewness and kurtosis values by their standard error is below 3.2 (Tabachnick & Fidell, 2007). According to this assumption, it is determined that the skewness and kurtosis values of the variables indicate normal distribution.

Table 10. Normality test results

Variables	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis	VIF
Seat Comfort	1	5	2.46	1.377	.416	-1.138	0.778
Cabin Staff Service	1	5	2.84	1.569	.120	-1.518	0.950
Food & Beverages	1	5	2.32	1.390	.598	-.995	0.950
Inflight Entertainment	1	5	2.25	1.253	.621	-.727	0.794
Wifi & Connectivity	1	5	2.36	1.234	.525	-.702	0,.902
Ground Service	1	5	2.45	1.565	.495	-1.349	0.689
Value for Money	1	5	2.63	1.616	.369	-1.484	0.832

Following the normality test, the multiple regression analysis results are presented in Table 11.

Table 11. Multiple regression analysis results

Dependent Variable	Independent Variable	B	Std. Error	β	t	p
Overall Rating	Seat Comfort	.123	.010	.104	11.891	.000
	Cabin Staff service	.132	.009	.127	14.095	.000
	Food & Beverages	.117	.010	.099	11.373	.000
	Inflight Entertainment	.020	.009	.016	2.182	.029
	Wifi & Connection	-.004	.009	-.003	-.439	.661
	Ground Service	.253	.009	.243	27.634	.000
	Value for Money	.448	.010	.444	44.799	.000
Adjusted R^2= 0.845	Estimated Standard Error =0.642	Anova (p)= 0.000	F= 4414.235	R^2= 0.845		

Table 11 presents that 84.5% of variance in the dependent variable (rating scores) can be explained by independent variables (seat comfort, cabin staff service, food & beverages, inflight entertainment, wifi & connection, ground service and value for money). Therefore, H_2 hypothesis is supported. The individual variable relationships assessment leads to following conclusions:

- Seat comfort, cabin staff service, inflight entertainment, ground service and value for money variables affect rating scores statistically significantly ($p<0.05$). While wifi&connection variable has a non-significant relationship with the rating score.
- The increase of one unit standard deviation in independent variables affect rating score with following levels: seat comfort 10.4%, cabin staff service 12.7%, food &

beverages 9.9%, inflight entertainment 1.6%, ground service 24.3% and value for money 44.4%.
- The highest impact belongs to value for money variable and it is followed by ground service, cabin staff service, seat comfort, food & beverages. The lowest impact belongs to inflight entertainment.

4.3. Anova Tests for Travel Type And Travel Class

Following the regression analysis focusing on causal relationship, the difference tests for travel type and travel classes regarding the rating score and recommendation status are employed. Tables 12 and 13 show ANOVA test results for rating scores, while Tables 14 and 15 present the ANOVA test results for recommendation status.

Table 12. Anova test results for rating scores differences in travel type groups

Variable	Variance Source	Sum of Squares	df	Mean Square	F	Sig.
Rating Scores	Between Groups	383.441	3	127.814	10.844	.000
	Within Groups	66808.212	5668	11.787		

(I) Travel Type	(J) Travel Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	95% Confidence Interval
					Lower Bound	Upper Bound
Solo Leisure	Couple Leisure	.337*	.114	.017	.04	.63
	Family Leisure	.243	.123	.197	-.07	.56
	Business	.851*	.152	.000	.46	1.24
Couple Leisure	Solo Leisure	-.337*	.114	.017	-.63	-.04
	Family Leisure	-.095	.124	.871	-.41	.22
	Business	.514*	.153	.004	.12	.91
Family Leisure	Solo Leisure	-.243	.123	.197	-.56	.07
	Couple Leisure	.095	.124	.871	-.22	.41
	Business	.609*	.159	.001	.20	1.02
Business	Solo Leisure	-.851*	.152	.000	-1.24	-.46
	Couple Leisure	-.514*	.153	.004	-.91	-.12
	Family Leisure	-.609*	.159	.001	-1.02	-.20

Table 12 indicates that airline passengers' travel rating scores differ between travel types statistically significantly ($p<0.05$), therefore H_3 hypothesis is supported. The following conclusions are confirmed by Table 12:

- There is a significant difference between solo leisure type and couple leisure types in rating scores and solo leisure type passengers' rates higher than couple leisure type passengers.
- Solo leisure and business type users significantly differ in rating scores, and solo leisure type passengers' rate higher than business type passengers.

- There is a significant difference between couple leisure and business types in rating scores, while the couple leisure passengers' rate higher than business type passengers.
- Family leisure type passengers and business type passengers have significant differences in rating scores. Family leisure type passengers' rate is higher than business type passengers.

Table 13 examines the rating score with travel classes (seat types) and concludes significant differences ($p < 0.05$) between travel classes that confirm the support of H_4 hypothesis.

Table 13. Anova test results for rating scores differences in travel class groups

Variable	Variance Source	Sum of Squares	df	Mean Square	F	Sig.
Rating Scores	Between Groups	428.486	3	142.829	12.126	.000
	Within Groups	66763.167	5668	11.779		

(I) Travel Class	(J) Travel Class	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
First Class	Economy Class	1.494	.953	.397	-.96	3.94
	Business Class	.126	.985	.999	-2.41	2.66
	Premium Economy	.804	.985	.847	-1.73	3.34
Economy Class	First Class	-1.494	.953	.397	-3.94	.96
	Business Class	-1.368*	.259	.000	-2.03	-.70
	Premium Economy	-.690*	.259	.039	-1.36	-.02
Business Class	First Class	-.126	.985	.999	-2.66	2.41
	Economy Class	1.368*	.259	.000	.70	2.03
	Premium Economy	.677	.360	.237	-.25	1.60
Premium Economy	First Class	-.804	.985	.847	-3.34	1.73
	Economy Class	.690*	.259	.039	.02	1.36
	Business Class	-.677	.360	.237	-1.60	.25

Table 13 indicates the significant difference between business class and economy class passengers, while the business class passengers' rate is higher than economy class passengers. It is also concluded that, there is a significant difference between premium economy class and economy class passengers as the premium economy class passengers have higher rating scores than economy class passengers.

Table 14 presents ANOVA test results for recommendation status in travel type groups and concludes significant differences (p<0.05) between groups. Therefore, H_5 hypothesis is supported.

Table 14. Anova test results for recommendation status in travel type groups

Variable	Variance Source	Sum of Squares	df	Mean Square	F	Sig.
Recommend	Between Groups	8.229	3	2.743	11.951	.000
	Within Groups	1300.851	5668	.230		

(I) Travel Type	(J) Travel Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Solo Leisure	Couple Leisure	.057*	.016	.002	.02	.10
	Family Leisure	.036	.017	.152	-.01	.08
	Business	.122*	.021	.000	.07	.18
Couple Leisure	Solo Leisure	-.057*	.016	.002	-.10	-.02
	Family Leisure	-.021	.017	.619	-.07	.02
	Business	.065*	.021	.013	.01	.12
Family Leisure	Solo Leisure	-.036	.017	.152	-.08	.01
	Couple Leisure	.021	.017	.619	-.02	.07
	Business	.086*	.022	.001	.03	.14
Business	Solo Leisure	-.122*	.021	.000	-.18	-.07
	Couple Leisure	-.065*	.021	.013	-.12	-.01
	Family Leisure	-.086*	.022	.001	-.14	-.03

Table 14 concludes the significant differences in recommendation status between solo and couple leisure type passengers, while solo passengers are more likely to recommend. Differences between solo leisure type and business type passengers are also included, while solo leisure type passengers tend to recommend more. The other differences take place between couple leisure passengers & business passengers' and family leisure passengers & business passengers. Both couple leisure passengers and family leisure passengers tend to recommend more than business passengers.

Table 15 concludes the significant difference (p < 0.05) between travel classes for recommendation variable. Therefore, H_6 hypothesis is supported. It is found that there is a significant difference between economy class passengers and business class passengers for recommendation variable. Business class passengers tend to recommend more than economy class passengers.

Table 15. Anova test results for recommendation status in travel class groups

Variable	Variance Source	Sum of Squares	df	Mean Square	F	Sig.
Recommend	Between Groups	5.056	3	1.685	7.326	.000
	Within Groups	1304.023	5668	.230		

(I) Travel Class	(J) Travel Class	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	95% Confidence Interval
					Lower Bound	Upper Bound
First Class	Economy Class	.184	.133	.511	-.16	.53
	Business Class	.027	.138	.997	-.33	.38
	Premium Economy	.135	.138	.760	-.22	.49
Economy Class	First Class	-.184	.133	.511	-.53	.16
	Business Class	-.157*	.036	.000	-.25	-.06
	Premium Economy	-.049	.036	.532	-.14	.04
Business Class	First Class	-.027	.138	.997	-.38	.33
	Economy Class	.157*	.036	.000	.06	.25
	Premium Economy	.108	.050	.141	-.02	.24
Premium Economy	First Class	-.135	.138	.760	-.49	.22
	Economy Class	.049	.036	.532	-.04	.14
	Business Class	-.108	.050	.141	-.24	.02

5. Conclusion

The study focuses on the LCC airlines customers eWOM behavior by examining the user reviews on airlinequality.com data and employs logistic regression, linear regression and difference test methodologies to evaluate the context. Evaluating airline reviews data on Skytrax / airlinequality.com for airline research is studied in several contexts in the current literature (Lucini et al., 2020; Song et al., 2020; Farzadnia & Vanani, 2022; Wang et al., 2023b). This study extends the literature to LCC airline companies with a specific context approach.

The first part of the research indicates determinants of users' recommendation expression in user reviews. Assessing the determinants in LCC cost specifically can be helpful for extension of the literature in specific LCC areas. The findings of the first part reveal that, according to the sizes of the standardized regression coefficients, the value of money variable has the most significant impact, followed by ground service, cabin staff service, seat comfort and food & beverages variables. Accordingly, it is determined that the variability on the dependent variable is explained by the independent variables considered within the scope of the study, seating comfort, personnel service, food quality, ground service and value for money, at a rate of 87.50% (Nagelkerke R^2) and 63.90% (Cox and Snell R^2), respectively, according to two different methods. This value being over 50% is considered very important, especially in social sciences (Streiner, 1994). However, the entertainment and wifi variables have a wald value below 2 and significant values. Therefore it is found that the values are not statistically significant. Non-significant impact of entertainment is confirmed in the previous literature (Ban & Kim, 2016).

The second part continues with the relationship of user review variables with the rating score (from 1 to 10) and it concludes the specific degree of effects of determinants. The most crucial factor of the rating score is concluded as value for money, followed by ground service. Value for money finding confirms the previous literature (Mutlu & Sertoğlu, 2018; Ban & Kim, 2019; Brochado et al., 2023). The findings confirm the utilitarian side of LCC airline companies, as consumers focus

on the utilitarian side more than the hedonic sides such as inflight entertainment. Insignificant relationship between wifi & connectivity also confirms the utilitarian side of the consumers.

The last part of the study focuses on the same dependent variables (recommendation status and rating scores) by comparing the travel type and seat types. The last part of the analysis reveals that business travel type users and economy class passengers have the lowest values among the other groups regarding recommendation status which is consistent with LCC airline passengers' nature in terms of economical tendencies. Traveler types examination leads to the conclusion that solo leisure type of travelers have a higher tendency to rate higher and recommendation. Travel class examination concludes a novel finding that first-class users using LCC airlines tend to rate higher and recommendation. On the other side of travel class types, economy class users have the lowest rating scores and recommendation levels. Differences between the first class and the economy classes are already included in previous studies (Punel et al., 2019). In addition, the difference between travel classes is also related to expectancy/satisfaction relationship in consumer behavior research. The expectancy levels of users can affect their rating scores and recommendation statuses.

For the managerial results of the study; eWOM phenomenon is a crucial element in digital marketing in the airline marketing industry and specific contexts - the result of having distinct characteristics- can make use of eWOM for; i) a better understanding of users' experiences, ii) detecting the gaps / effective areas in the existing attributes, iii) discovering the competitive opportunities (in terms of market analysis). From this point of view, airline marketing decision-makers must examine eWOM conversations regularly and prepare improvement/solution-fixing mechanisms for eWOM conversations. Therefore, eWOM can cause consumers to have different judgments about the quality of service due to their cultural status, past experiences, people around them, and relatives. Therefore, consumers are affected by the opinions of people around them from whom they receive similar services, live in similar conditions, or have similar cultural characteristics (Ateşoğlu & Bayraktar, 2011). In addition,

consumers constantly tell each other about their experiences in daily life, and today, it has become easier to get and give advice thanks to the internet. eWOM is gaining importance in terms of consumers communicating with their social circles and acquaintances as well as strangers and reaching the information they want thanks to the internet (Ezzatirad, 2014).

Although online reviews and airlinequality.com content may signal much information regarding eWOM behaviors of airline consumers, eWOM ecosystem is not limited to online reviews. Social media posts, user reviews/comments on video channels and complaint systems on the global web can be integrated for further research studies. The inclusion of additional eWOM sources can be helpful n comprehensively evaluating the customers. The second future research direction is related to the extension of methodologic approaches, as the new technological advances in methods can be helpful to academic research and make sense of digital content. Analytical approaches such as sentiment analysis, machine learning, AI-supported systems can be helpful for future research studies in LCC airline context.

Traditional methods were used in this study. In addition to this research, future researchers can perform analyses using text mining and sentiment analysis techniques. However, the data in this study is relatively small, so research can be conducted with a more significant amount of data. In addition, although there is limited study on this subject, Alanazi et al. (2024) used approximately 7500 reviews from Skytrax to explore the determinants of airport service quality and their effects on passenger recommendations. They examined various features such as terminal cleanliness, terminal seating arrangement, terminal signs, food and beverages, airport shopping, WiFi connection and airport staff. Although the basic structure of the study is similar to Alanazi et al.'s study, in this study, within the scope of the service factor of the passengers: seat comfort, cabin crew service, food and beverage service, in-flight entertainment service, WiFi and connectivity service, ground service and monetary value of the service received were evaluated. As a result, it was determined that the scores given by the airline users for seat comfort, cabin crew service, food and beverage service, in-flight entertainment service, WiFi and connectivity service, ground service and monetary value of the service received affect the user's recommendation and play an essential role in their evaluations. In particular, it was determined that the passengers who recommended airline travel were more likely to perceive cabin crew service and ground service in addition to other service factors in the study. While Maldonado (2024) emphasizes that passenger satisfaction is primarily affected by the behavior of airline personnel (being friendly, warm-hearted, etc.) regarding airline passengers' recommendations, this study examines the impact of seat comfort, cabin crew service, food and beverage service, in-flight entertainment service, wifi and connection service, ground service, and the points given by airline passengers for the monetary value of the service on the user's recommendation and it has been determined that passengers are affected by these factors in these evaluations.

In light of the findings, recommendations for airline companies and marketers are expressed below.

The recommendations for the airline company are presented below:

➢ Investment should be made in seat design and comfort so that passengers can be comfortable even on long flights.

➢ The staff's education level should be increased, customer relations skills should be developed and personalized services should be provided to passengers.

➢ Menu options should be expanded, quality products should be used and special dietary needs should be considered.

➢ Passengers should avoid boredom during the flight by offering up-to-date and diverse entertainment options.

➢ WiFi and connection: A reliable and fast internet connection should be provided, allowing passengers to do their work or have fun.

➢ Check-in, baggage delivery and other ground service processes should be accelerated and seamless.

Suggestions for marketers are presented below.

➢ Detailed analyses should be conducted to determine the needs and expectations of consumer passenger types and marketing campaigns specific to these segments should be created.

➢ Personalized offers and suggestions should be provided using consumer data.

➢ Effective loyalty programs should be developed and reviewed regularly to increase consumer loyalty.

➢ Regional marketing strategies should be developed considering passengers' expectations and preferences in different regions.

In the study, the evaluations of users in the airline sector were tested more comprehensively with a mixed method combining both quantitative and qualitative data. It focuses on the airline sector, a more specific sector than other studies and offers the opportunity to examine users' thoughts and behaviors from different perspectives. Thus, it tries to follow the most current trends in the airline sector and shed light on the literature.

Ethical approval
Not applicable.

Conflicts of Interest
The authors declare that there is no conflict of interest regarding the publication of this paper.

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