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Research Article

Investigating The Leisure Airline Market through Consumer Feedback: A Sentiment Analysis on User Reviews

Tüketici Geri Bildirimleri Üzerinden Tatil Havayolu Pazarını Araştırma: Kullanıcı Değerlendirmeleri Üzerine Bir Duygu Analizi

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Abstract

The airline market, characterized by high competition, globalization and diverse user expectations, necessitates understanding consumers and evaluating their feedback. In line with the unique characteristics of the leisure airline market, this study aims to examine the market through user reviews. A sample of 3,571 user reviews of 10 airlines on the Skytrax (Airlinequality.com) website was used for this study and sentiment analysis was applied to examine the sentiments expressed in these reviews, utilizing 3,489 user reviews. The descriptive analysis concluded that user reviews for leisure airlines were generally dominated by negative ratings, with rating polarization differing among airlines. During the sentiment analysis phase of the study, the primary emotions found in user reviews were neutral (24.7%), disgust (21.3%) and sadness (14.9%). The feelings expressed in these reviews were surprising (11.5%), fear (10.9%), joy (9.9%) and anger (6.7%). The study provides an examination of the leisure airline market that can guide industry decision-makers in market insights through user reviews.

Keywords: *Airline Marketing, Leisure Airlines, Online Review, Word of Mouth, Consumer Behavior*

Özet

Yüksek rekabet, küreselleşme ve farklı kullanıcı beklentileri gibi değişkenlere sahip havayolu pazarı, tüketicileri anlamayı ve geri bildirimlerini değerlendirmeyi gerekli kılmaktadır. Tatil havayolu pazarının kendine özgü özelliklerine uygun olarak bu çalışma, pazarı kullanıcı yorumları aracılığıyla incelemeyi amaçlamaktadır. Çalışmada Skytrax (Airlinequality.com) web sitesinde 10 havayolu şirketine ait 3571 kullanıcı değerlendirmesi örneklem olarak alınmış ve değerlendirmelerde yer alan duyguları incelemek için uygulanan duygu analizi yönteminde 3489 kullanıcı değerlendirmesi kullanılmıştır. Tanımlayıcı analiz aşamasında çalışmada, tatil havayolları için kullanıcı yorumlarında genel olarak olumsuz derecelendirme puanlarının baskın olduğu ve havayolu şirketleri arasında derecelendirme puanı kutuplaşmasında farklılıklar olduğu sonucuna varılmıştır. Çalışmanın duygu analizi aşamasında, kullanıcı yorumlarında nötr duygu (%24,7), iğrenme duygusu (%21,3) ve üzüntü duygusu (%14,9) başlıca duygular olarak bulunmuştur. Kullanıcı yorumlarında yer alan duygular sırasıyla sürpriz duygusu (%11,5), korku duygusu (%10,9), neşe duygusu (%9,9) ve öfke (%6,7) duygusu olarak sıralanmıştır. Çalışma, kullanıcı yorumları aracılığıyla pazar içgörüleri konusunda sektördeki karar vericilere yol gösterebilecek bir tatil havayolu pazarının incelemesini sunmaktadır.

Anahtar Sözcükler: *Havayolu Pazarlaması, Tatil Havayolları, Çevrimiçi Değerlendirme, Ağızdan Ağıza Pazarlama, Tüketici Davranışı*

1. INTRODUCTION

The airline industry, one of the most important sectors affecting global trade, tourism and cultural interaction, has a critical economic role today. According to IATA (2025), the revenue of the global airline industry in 2023 is $908 billion, while there are 35.7 million flights in 2023. In the airline industry, where there was relatively less competition in the early days, the intensity of competition has increased with the increase in new brands and global routes and understanding consumer needs has become an important point. Understanding consumers with different needs and expectations is essential for airlines competing in the market. The airline industry offers different research contexts for today's marketing research, with different product options and presentation formats that appeal to different types of consumers.

As one of the different consumer groups in the airline market, leisure passengers are characterized by different characteristics and different priorities compared to other passengers. Martínez-Garcia et al. (2012) examine the business travelers and leisure travelers by low cost carriers context in their study and conclude that I) business travelers stay shorter time period and has fewer activities, ii) low fare of low cost carriers is found most valued attribute for both business travelers and leisure travelers, iii) greater experience with low cost carriers for the leisure travelers is associated with airport proximity to destination and flight quality, not with the price. In the micro aspect, this consumer group can be summarized as a group with expectations such as lower prices and discounts and in the macro aspect, as a group that experiences periodic demand changes and focuses more on tourist places. Based on these differences, there are also differences in the marketing mix and marketing communication activities for this user group. Lu et al. (2022) examine US airline data collected from social media (Twitter) and non-social media (Skytrax) platforms between 2014 and 2019 using specialized text mining techniques to identify service quality metrics by presenting a method based on importance-performance analysis. Murugesan et al. (2024) conduct a study on the Skytrax Airline Reviews dataset and the LightGBM model with nine different machine learning algorithms, aiming to predict passenger satisfaction by integrating sentiment and ratings in reviews. Since the majority of the studies focus on traditional airline companies in terms of full-service and business contexts, the research on the leisure airline context is limited. This study focuses on this research gap and examines online reviews to examine the Users' side in the market.

The study aims to extend the airline marketing and eWOM concept into the leisure airline marketing context by examining the user reviews on the Skytrax - Airlinequality.com platform (Skytrax, 2025a). In addition to the theoretical side, the study also employs a transformers-based sentiment analysis methodology as a methodological novelty and aims to detect the sentiments in the user reviews to examine the emotional side of the user reviews. For these purposes, 3571 reviews of 10 airline companies are collected as a sample and 3489 reviews are used in the sentiment analysis.

The study starts with a theoretical section consisting of airline marketing/airline customer and electronic word-of-mouth concepts as the conceptual basis for the study. The sample and methodology section, followed by the findings and discussion section, is the second part and the conclusion section, consisting of theoretical contributions and practical implications, finalizes the study.

2. CONCEPTUAL BACKGROUND

2.1. Airline Marketing and Customer

Airline marketing is one of the most important economic markets, characterized by high competition, diverse consumer groups and various product options. Globalization and increased competition with the entry of new airlines have made effective marketing decisions and consumer decision-making essential for airline companies. In essence, airline companies must identify their customers well and answer their needs to continue in the competitive environment in the market (Punel & Ermagun, 2018). As Leon and Dixon (2023) point out, satisfied and loyal customers can be the determinants for companies in the market environment where the competitiveness is high and profit margins are low. Chang and colleagues (2022) complement existing approaches to sentiment analysis in the airline industry; they expand the use of data-driven and visualization-based analytical methods to gain a deeper understanding of customer satisfaction during the COVID-19 pandemic. Shahid and colleagues (2024) develop machine learning models to predict the likelihood of customers repurchasing airline services by combining sentiment analysis and LIWC-based features with user experience elements. The study highlights the impact of emotional ties on loyalty; the XGBoost algorithm provides the most successful prediction model with an accuracy rate of 85%. The findings demonstrate the strong potential of machine learning in understanding customer behavior, helping airlines shape their services and strategies more effectively.

On the business side, meeting the expectations of passengers leads to an increase in passenger satisfaction and value perception (Park et al., 2004). Park et al. (2019) indicate that retention of customers is much important than gaining new customers for most airlines in the global airline environment. Retention of customers is related to understanding the reactions of consumers which leads to the requirement of monitoring the online available data in the market. Customer-driven evaluation of services, which contains the knowledge of which services lead to gaining more passengers, should be used bir airline companies to improve services (Noviantoro & Huang, 2022). Therefore, the customer is the significant factor in airline marketing. Farzadnia & Vanani (2022) analyzed passenger reviews of the top 10 airlines in the Middle East and identified strengths and weaknesses in service delivery through sentiment analysis. Based on the findings, specific recommendations were made based on the satisfaction level for each airline and it was emphasized that these recommendations could guide marketing strategies to increase customer acquisition and market share. Since a crucial element for the airline companies for improving the competitiveness in a saturated market relates to customers’ perception regarding airline company to be customer-centric (Soklaridis et al., 2024), understanding the marketplace through customer data -as a part of being customer-centric- is essential. Becoming customer-centric involves familiarizing with customer research and feedback monitoring in the digital age. Previous airline marketing studies examine the digital channels and relevant customer concepts in several contexts such as social media marketing activities (Seo & Park, 2018), Twitter data and market segments (Punel & Ermagun, 2018), customer complaints during Covid-19 (Çallı & Çallı, 2023). Gitto and Mancuso (2017) apply sentiment analysis to blog data to assess customer satisfaction at five airports. The study reveals that passenger comments focus on non-aviation services such as food, beverages and shopping.

Online platforms and information on digital platforms contribute to the understanding of the marketplace, since they contain insights about consumers, product and service evaluations and market. The users can share their reviews and feedback directly with the airline companies or share with other social media users, which leads to a large scale of communication. Therefore, examination of communication on digital platforms has potential for airline marketing decision-makers. Higgins (2022) highlights the strategic importance of deriving customer insights from tweet data for airlines, discussing the potential of these insights to improve service, differentiate from competitors and provide a competitive advantage based on customer sentiment analysis. The study achieves 71% accuracy using the Naïve Bayes algorithm. Hasib et al. (2024) provide a comprehensive overview of widely used datasets and machine learning and deep learning models applied to these datasets, covering key application areas, including multilingual sentiment analysis in the airline industry. The literature review reveals key insights into sentiment analysis by critically evaluating the strengths and weaknesses of methods in the field.

2.2. Electronic Word of Mouth

The classical concept of word of mouth as *"informal communications directed at other consumers about the ownership, usage, or characteristics of particular goods and services and/or their sellers"* (Westbrook, 1987) is one of the crucial concepts in consumer research. With the help of the advances in technology and proliferation of social media, the communication between parties takes place between the users around the world through the internet. Leading to the electronic word of mouth (eWOM) concept area in marketing research, it becomes crucial to evaluate the several aspects of user communication online.

The scope of eWOM concept is quite extensive due to complexity of information sources, mediators and people-related factors. Litvin et al. (2008) examine the literature and present a conceptual model regarding eWOM. According to authors, consumption experience and mass media are the sources for eWOM, while outcomes of eWOM contain customer loyalty, product evaluation, purchase decision, consumer empowerment and product acceptance. Discovering the factors influencing consumer opinions and behaviors is crucial in this context. On the consumer side, Bickart and Schindler (2001) compare the influential effect of online discussions and marketer-generated online information in their study, and they report a more influential effect by online discussions. Trusting and relying on others' comments on product and service topics is a determinant for eWOM research, which leads to the necessity of understanding the content of the eWOM communication.

In the business perspective, electronic word of mouth contains various information sources online such as online reviews, social media posts and user-generated content on multimedia forms. Previous studies in the literature examine various aspects of eWOM such as online review helpfulness (Baek et al., 2012; Siering et al., 2018), customer satisfaction (Zhao et al., 2019) and drivers of it on social networking sites (Wang et al., 2016). In addition, the relationship among content-related variables has already been examined in several scenarios, such as content length with demand (Fink et al., 2018), content depth and content deviation with review helpfulness (Wu et al., 2021), and numerical and textual characteristics with review helpfulness (Zhou & Yang, 2019). The content side of the online reviews contains several variables, while the topic and emotion included are the main components in this aspect. In the first component, directly expressed or latent topics can be discovered using methodologies such as topic modeling and text mining. For example, Hu et al. (2019) employ a structural topic modeling approach to discover the topics in the hotel industry and identify 10 negative topics. In the second component, expressed emotions in polarity form (such as positivity, negativity or neutrality) or in specific emotion categories can be detected through methodologies such as sentiment analysis. For example, Mostafa (2013) uses 3516 tweets of Twitter posts to examine the sentiments about famous brands and concludes generally positive consumer sentiment towards several brands. In another study, Ghadi et al. (2025) employ a sentiment analysis approach for user reviews in the banking industry by utilizing 20,137 Trustpilot reviews. User reviews may convey the emotional expression of the users, which can be a signal for customer insights.

Lee and Jang (2017) assess customer satisfaction through social media data by analyzing 77,591 tweets from two full-service (FSC) and six low-cost (LCC) airlines between 2008 and 2016. The findings reveal that LCCs provide significantly higher customer satisfaction than FSCs ($p<0.001$), while satisfaction levels for both carrier types have steadily decreased over the years. Furthermore, low satisfaction is reported in service areas such as reservations and flight operations, while a significant decline is observed in in-flight services, reservations and marketing for FSCs. Martin-Domingo et al. (2019) analyze Twitter data from London Heathrow Airport to examine how sentiment analysis (SA) techniques can contribute to the measurement of Airport Service Quality (ASQ). The study revealed significant differences in the frequency with which passengers refer to specific attributes on the ASQ scale; identifying these differences provides key insights for strategic decisions to improve service quality. Li et al. (2023) evaluate the sentiment classification performance using BERT and its three variants on tweet data related to the airline industry. The findings show that these models are effective in analyzing customer sentiment. In particular, RoBERTa was the most successful model, achieving the highest accuracy rate in binary (96.97%) and ternary (86.89%) classification tasks and exhibiting superior performance on balanced datasets. Md Saad et al. (2023) use sentiment analysis, thematic analysis and word frequency methods to assess consumers' perceptions of AirAsia services in the post-COVID-19 era. The study, conducted using NVivo software, reveals that negative sentiments are more dominant than positive sentiments, which are low in all customer satisfaction dimensions. Yenkikar and Babu (2023) use AirBERT, a deep learning model with an attention mechanism, in addition to traditional machine learning algorithms, in their multi-class sentiment analysis of Twitter data belonging to five Indian airlines. While TF-IDF-aided random forest is the most successful conventional method, the AirBERT model performs best with 91% accuracy. According to the sentiment distribution results, the most positive comments are reported for Indigo, while the most negative comments are recorded for Jet Airways. Mahmud et al. (2024) demonstrate the high capacity of these models in contextual language processing using transformer-based models, including DistilBERT, RoBERTa, ALBERT, Electra and basic and major versions of BERT. Although the performance results are generally similar, the ALBERT model performs slightly lower with 97% accuracy on the dataset studied; however, this continues to highlight the effectiveness of transformer architectures on complex language structures. Yadav et al. (2024) aim to develop an advanced sentiment analysis process using transformation-based models such as BERT, RoBERTa and DistilBERT to analyze emotional expressions in airline inspection reviews. Integrating AI and text mining techniques aims to accurately classify the content and tone of positive and negative feedback expressed in user reviews. Accordingly, the study seeks to contribute to deepening industry insights by separating emotional differences regarding airline passengers' experiences. Lee and Jang (2017) examine customer satisfaction on social media by analyzing 77,591 tweets for two FSC and six LCC airlines between 2008 and 2016. The results show that LCCs provide significantly higher satisfaction than FSCs ($p<0.001$), but satisfaction decreases over time for both types of carriers. Complaints regarding reservations and flight operations are particularly prominent, while satisfaction with in-flight services, reservations and marketing decreases significantly for FSCs.

Online reviews data and the electronic word of mouth concept are evaluated in airline marketing research in several studies. Ban and Kim (2019) use 9632 Skytrax user reviews in their study and they conclude the variables as factors for customer satisfaction and recommendation. In another study, Lim and Lee (2020) examine user reviews by service quality perception lens, while they implement topic modeling and match the extracted topics with service quality dimensions. They conclude that for full-service carriers and low-cost carriers, tangibles and reliability dimensions are the most significant dimensions, while assurance and empathy are the least significant dimensions. Murugesan et al. (2024) conduct a study on the Skytrax Airline Reviews dataset, aiming to predict passenger satisfaction by integrating sentiment and ratings in reviews. The LightGBM model shows the highest success with 97% accuracy in the analysis conducted with nine different machine learning algorithms. The findings reveal that the most influential factors in satisfaction are "Value for Money" and "ground service." In contrast, the "fun" factor does not play a decisive role. This study examines reviews on the Skytrax - Airlinequality.com (Skytrax, 2025a) website to evaluate the leisure airlines context.

3. METHODOLOGY

Airlinequality.com (Skytrax, 2025a) provides a platform for users to write reviews about airline companies and the reviews can be a helpful source for extracting insights regarding the market. Consistent with the research aim, the study employs user reviews on Airlinequality.com (Skytrax, 2025a). Selection of airline companies for the study uses two sources to create a list of leisure airline companies. "World's Best Leisure Airlines 2024" list (Skytrax, 2024) announced by Skytrax is used as the base list, then the airline companies filter page on skytraxratings.com web page (Skytrax, 2025b) is used. The combined list consists of 10 airline companies as the airline sample of the study.

Data collection stage employs Python programming language (Van Rossum & Drake, 1995) on Google Colab platform (Google, 2025). Data collection takes place on 23.02.2025. 3571 reviews from 10 airline companies are retrieved as a sample of the study. Since some of the reviews are quite long to process in transformer-based sentiment analysis, 82 rows are dropped, and a total of 3489 reviews are used in the study for sentiment analysis.

Table 1. Sample of the Study

Company	N	Company	N
Air Canada rouge	1160	TUI Airways	90
Air Transat	778	SunExpress	87
Sunwing Airlines	727	TUIfly	74
Condor Airlines	484	Corsair International	43
Edelweiss Air	108	Nouvelair	20
Total Reviews		3571	

Descriptive statistics are calculated in the first stage of the analysis. In this stage, the overall rating score distribution, the rating score distribution by companies and the distribution of rating categories are examined. Following the first stage, sentiment analysis is employed in the second stage, containing the distribution of sentiment scores. The first stage examines the descriptive information of user reviews, while the second stage focuses on the text content and processes the textual data.

Process of text data in an emotion perspective is related to sentiment analysis methodology that is defined by Medhat et al. (2014) as *"the computational study of people's opinions, attitudes and emotions toward an entity"*. According to Prabowo and Thelwall (2009), the methodology lets companies estimate the extent of product acceptance and determine the strategies for product quality improvement. At its most basic, words and patterns are matched and calculated with various polarities or specific emotions. For example, the sentence "I like this airline a lot" can be paired with the word 'like' and the word "much" with positive polarity. On the other hand, it is possible to go beyond polarity and identify specific emotions by identifying words or patterns that represent specific emotions. Giatsoglou et al. (2017) criticize the lexicon-based approach for neglecting "latent manifestations of sentiment", since the lexicon-based approach does not consider the context. The authors indicate that word embedding-based approaches using vector representations of documents can capture the sentiments better, while they implement a hybrid approach in their study. This study follows a transformers-based model named "Emotion English DistilRoBERTa-base" (Hartmann, 2022), which is a novel approach and a fine-tune checkpoint version of "DistilRoBERTa-base" (Sanh et al., 2019), which is a distilled version of the RoBERTa-base model (Liu et al., 2019). According to Koroteev (2021), the representations of text with vectors neglect the semantic features of words. Devlin et al. (2019) propose the "BERT (Bidirectional Encoder Representations from Transformers") model that is designed for examining the text from both sides (left and right), leading to bidirectional representations. This type of model can be useful for a better understanding of the text content. In the implementation stage, the sentiment scores are calculated for each review and then the final sentiment decision is made based on the maximum score of the sentiment.

4. FINDINGS AND DISCUSSION

Figure 1 examines the overall rating score distribution in the sample. 90 reviews do not contain overall rating scores and 3481 reviews are used to evaluate the distribution evaluation.

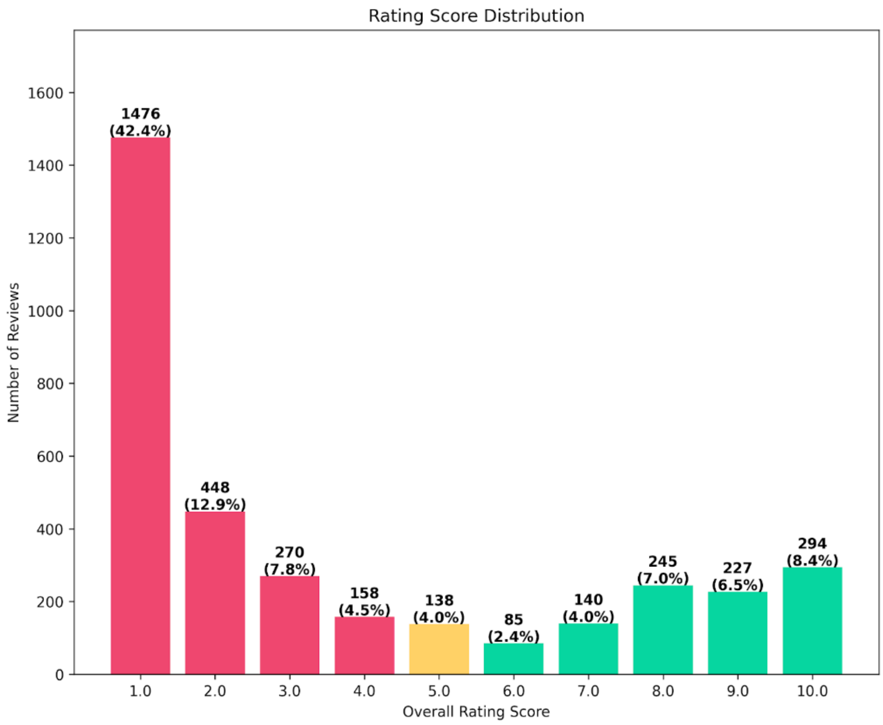

Figure 1. Overall Rating Score Distribution

According to Figure 1, 42.4% of reviews have a 1-rating score and the majority of the reviews are included in a negative zone, representing the dominance of negativity in the user reviews for leisure airlines. This negativity may signal unmet expectations or dissatisfaction regarding services/products. 28.3% of reviews are in the positive zone, representing the minority of positivity in the user reviews. 4% of 5-rating score reviews show that leisure airline user reviews have polarity. Following the interpretation of the overall distribution, it is useful to examine the airlines individually based on the negative, neutral and positive reviews.

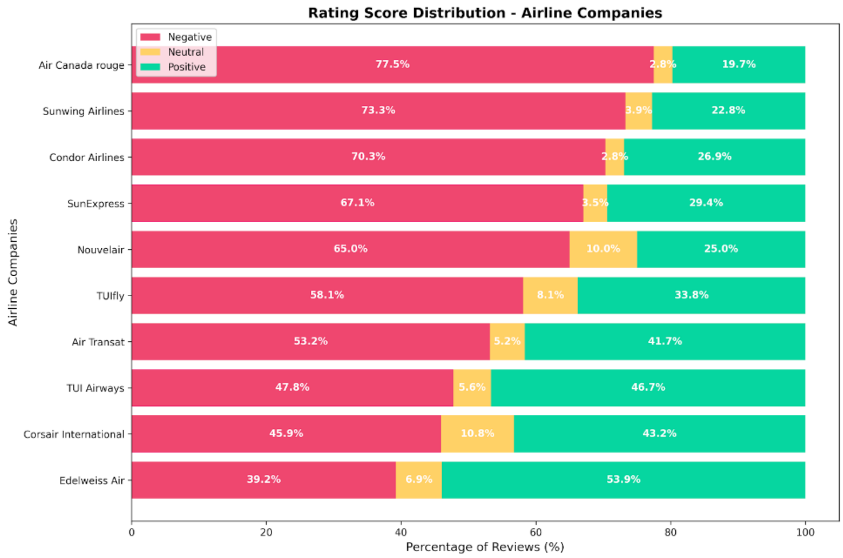

Figure 2. Rating Score Distribution by Airline Companies

Figure 2, showing the rating score distribution, presents the differences among the airline companies based on the distribution of rating scores. Airline companies like "Air Canada rouge", "Sunwing Airlines", "Condor Airlines", "SunExpress" and "Nouvelair" have negative reviews at more than 60% level, while "TUI Airways", "Corsair International" and "Edelweiss Air" have less than 50% level. This range difference is also valid for the positive side, since "Corsair International" has 43.2% positive reviews while "Condor Airlines" has 26.9% positive reviews.

In the next stage, review texts are converted into review_length variably by calculating the number of words included in reviews and the Spearman correlation test is implemented between review length and overall rating scores of the reviews. A statistically significant ($p < 0.05$) weak negative correlation (-0.1373) is concluded between the variables.

User reviews on Airlinequality.com contain several categories regarding seat comfort, cabin staff service, food & beverages, in-flight entertainment, ground service, wifi & connectivity and value for money. Figure 3 presents the average scores for each rating category in the sample.

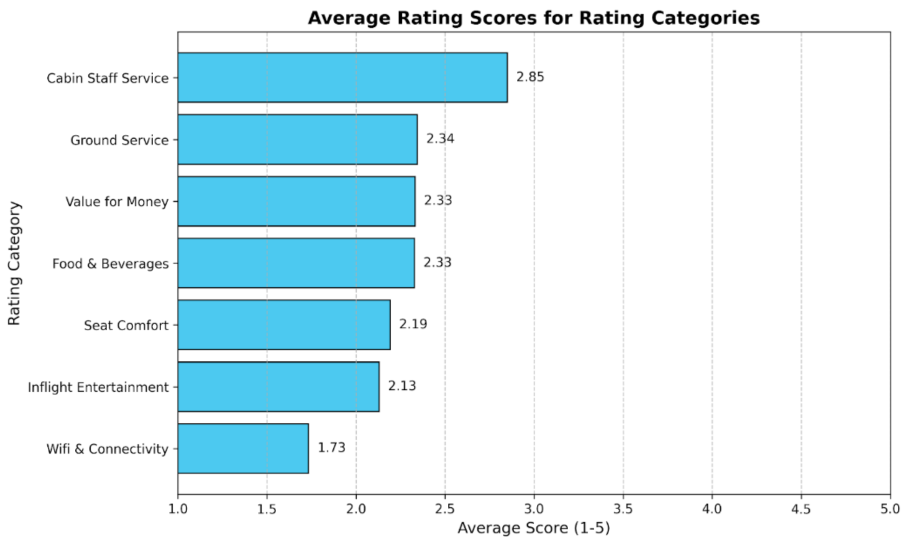

Figure 3. Average Rating Scores for Rating Categories

The first implication from the rating category score averages is that the average scores in the leisure airline context are generally close to average, but with low average levels. "Cabin Staff Service" has a 2.85 average score as the best performing rating category in the leisure airline context, while "Wifi & Connectivity" has the worst performing rating category by 1.73 average score. The relatively high levels in "Cabin Staff Service", "Ground Service"," Value for Money" and "Food & Beverages" represent the relatively successful side among other variables for the leisure airlines context.

Since the descriptive side of the analysis presents the overall structure of the leisure airline context, evaluation of the text content of the user reviews is useful for better understanding the emotional side of the users. Table 2 contains the sample reviews for each sentiment category, while Figure 4 reveals the distribution of the sentiment categories in the user reviews.

Table 2. Representative Reviews for Sentiment Categories

Sentiment	Sentiment Score	Review
Neutral	0.957	"Myself and a companion flew Air Transat on a one-way leg between Toronto Pearson Airport and London Gatwick. We chose Club Class, seats 1H, 1K. Club Class would be considered a poor man's business class; however, I believe that is an apples-to-oranges comparison. Transat's Club Class is more aligned to a Premium Economy product and that is the class I've denoted in the review profile. All considered, Club Class seats are fairly comfortable with generous width; pitch, however, is on the tight side (36"), particularly for the second of two rows that make up Club Class. The first row has a greater distance between the back of the chair and the bulkhead; however, these seats do not have a foot rest, as do the second row. Not having a footrest does make a difference over a longer flight; I recommend a portable (inflatable) footrest that will make a world of difference. Given a choice, choose the first row over the second as it is more spacious and you'll avoid a reclined chair invading your space. As well, go row 1 on the right side of the aircraft, as the one Club Class washroom is just adjacent to seats 1C and 1F. In-flight amenities include a blanket, a neck pillow, socks, slippers, a toothbrush with paste and headphones. The in-flight entertainment system is easy to use and full of films, shows, games, and music. The dining experience in Club Class is so-so. The cold meat plate offered on overnight flights is sparse and unappealing in look and taste. The only positive aspect is the hot soup offered. Breakfast in Club Class is similar, the best option is the cold breakfast which offers a varied fruit selection, yogurt, bran cereal and rolls. Avoid the egg dishes, bland and unappetizing. Service was very positive. Flight staff were professional, personable, friendly and present. Club Class pre-boarding is helpful as flights tend to be crowded and Terminal 3 (Toronto Pearson) organization of gates makes for chaotic boarding generally. While they may board first, Club Class passengers do not deplane first, but the delay to disembark is not a material one. In summary, Air Transat Club Class is a decent means of travelling longer distances in relative comfort and this particular flight proved it."
Disgust	0.990	"We flew with Air Transat to Vancouver on 9th September and returned on 24th September. We chose Option+; we were very disappointed with the food provided on this long-haul flight. Our inflight meal consisted of a pulled pork panini from the bistro menu, same on return flight. It was disgusting, near the end of the flight they then gave a piece of pizza. Coming home was even worse, breakfast consisted of a wet piece of cake, I think it should have been Madeira cake, but couldn't tell. I would advise you to take your own food on this flight. Also coming home it was a night flight and the heat on the plane was unbearable. I did ask for it to be turned down, but this never happened. We paid over £1500.00 for this flight and would not travel with them again."

Table 2. Representative Reviews for Sentiment Categories (continued)

Sentiment	Sentiment Score	Review
Sadness	0.983	"My sisters and I travelled from Toronto to Dublin with Air Canada rouge for a 2-week vacation. We were disappointed in the 'leisure' airline and the lack of leg room made it a very uncomfortable six-hour flight. The supper served was acceptable, but the breakfast was a cold slice of banana bread. We felt cramped, the app for accessing movies, etc was not up to much and we were generally feeling unhappy with this leisure airline. I would not book with Air Canada rouge again."
Suprise	0.983	"I flew from Frankfurt to Toronto for the first time in July. Although it was economy class, I was surprised by the good service food and the new interior design after reading a lot of negative reviews. However, the entertainment system should be free for all and then they would get 5 stars from me."
Fear	0.988	"Flew from Vancouver to LAX. Started to feel anxious once I sat in the seat and felt like I was in a strait jacket. My first thought was "how can an Airline treat it's paying customers like this". I am 5'10" and could not sit with my legs together as they would bump into the seat in front of me. I didn't care about the lack of food or entertainment because it was a short flight. I would be concerned about Deep Vein Thrombosis if I was on a longer flight. I will never fly Air Canada Rouge again unless it is in the Premium section."
Joy	0.988	"Flew to Florida on flight AC1860 May 2/14 at 6.30am return on 7th. I'll take the friendly service of this non- union staff any day of the week over that of the staff from its parent company. Onboard entertainment using your own device is a brilliant way to keep costs down. I'll forego a few first world luxuries over being treated like a third-class citizen. The cheery Rouge uniforms match that of their customer service. I'm excited to have an option under Aeroplan outside of AC."
Anger	0.975	"I did not know about this airline but was in a hurry so booked the Frankfurt - Calgary flight I usually fly good old Lufthansa. Now that I know it is a budget airline, I'm less furious about the extra fees on the baggage steep fee of $200 to upgrade to Econ premium $8 glass of wine condescending attendants and ground staff cramped space $8 extra headphone $8 to watch a movie. Let me put it this way: if you want to be penny wise pound foolish and don't mind bearing light humiliation from staff and service alike go ahead: Bon Voyage in the ultimate 10.5 hrs cattle class experience."

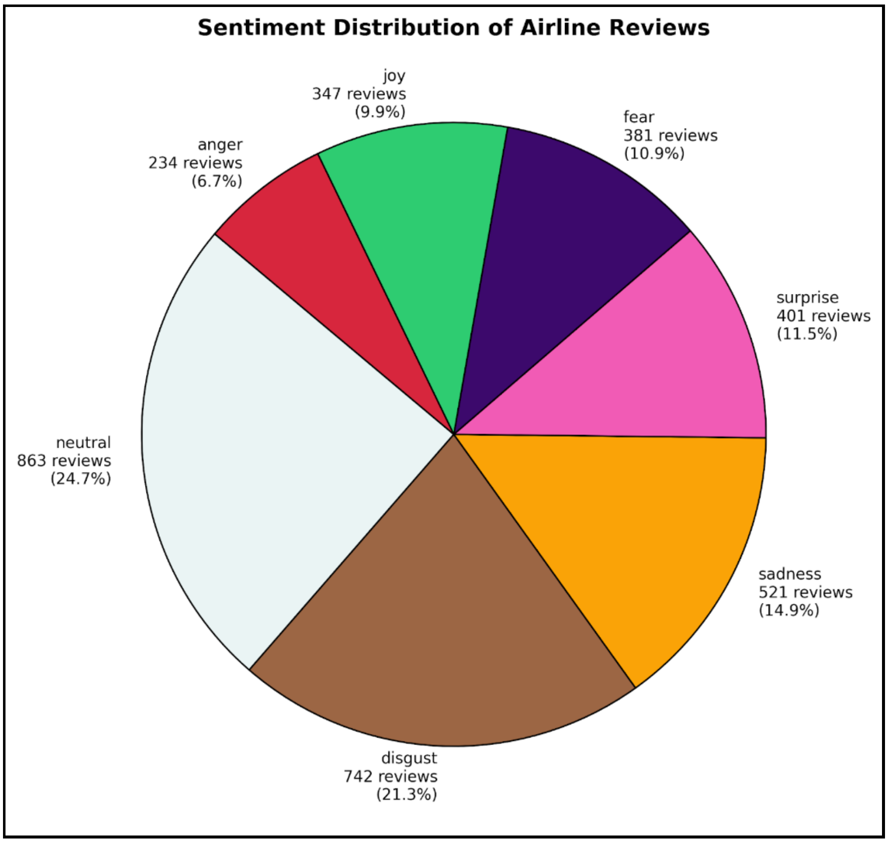

Figure 4. Sentiment Distribution of Airline Reviews

Figure 4, showing the distribution of sentiment categories in the reviews, presents neutral reviews (863 reviews) as 24.7% of the user reviews, the highest percentage. The neutrality can be related to several factors, such as mixed emotions, which contain positive and negative content in the same review, or the objectivity of the reviews. On the other hand, this implication shows that approximately 75% of the user reviews have non-neutral sentiment content, which is crucial for an emotional perspective.

Non-neutral part of the reviews poses potential emotion implications for the study. The first implication is related to the most dominant sentiment category, as 21.3% of user reviews have "disgust" sentiment category as the final sentiment in the reviews. Compared to other sentiment categories like "joy" and "surprise", the "disgust" category may be related to high negative expressions in the emotions. This level can be a signal for the expectation level of users in leisure airlines.

"Sadness" category with 521 reviews and "Fear" category with 381 reviews represent approximately 25% of the reviews. These sentiment categories have a distinct and non-specific nature, therefore they signal the necessity of further processing of the content for airline decision-makers. "Surprise" category with 401 reviews may also signal the unexpected experiences or expectation mismatch in the context. For example, the review in Table 2 mentions *"Although it was economy class, I was surprised by the good service, food and the new interior design after reading a lot of negative reviews."*. Leisure airline companies can process the specific category by examining the themes or topics and matching them to specific entities/actions in the user experience to improve their services. Finally, the "Joy" category with 347 reviews and the "Anger" category with 234 reviews have the lowest percentages in the user reviews, while "Joy" has 9.9% and "Anger" has 6.7% of the distribution.

CONCLUSION

The study examines airline marketing in the leisure airlines context through online reviews and employs sentiment analysis methodology to examine the emotional side of online reviews. Rating score distribution by overall rating scores and by airline companies is presented in the first stage, average scores for rating categories in the user reviews are examined in the second stage and the sentiment analysis results are included in the last stage.

The study contributes to the conceptual side by extending the airline marketing and eWOM concepts into the leisure airline context. Previous studies have examined the airline marketing and eWOM concept in several contexts. For example, Punel et al. (2019) studied different flight classes and geographical regions in their study. Song et al. (2020) focus on the flight delays context by examining user reviews through sentiment analysis methodology. In another study, Kwon et al. (2021) examine user reviews for airline companies in Asia and employ sentiment analysis and topic modeling together. However, this study examines the airline marketing through the leisure airlines context and concludes findings regarding the rating score distribution, rating categories distribution and sentiment analysis in the user reviews. The findings contribute to leisure airline-specific knowledge in the theory and eWOM research in airline marketing.

Employing sentiment analysis for the text content is crucial for text-based content like user reviews. Since Skytrax - Airlinequality.com (Skytrax, 2025a) website provides text content and rating scores together, evaluation of the emotional side can be helpful for marketing research. Previous studies already employ sentiment analysis in several aspects such as the COVID-19 pandemic (Pereira et al., 2023), pre-and post-pandemic comparison (Idris & Mohamad, 2024), and flight delays (Song et al., 2020). This study uses a transformer-based sentiment analysis methodology as a novel methodology in sentiment analysis and contributes to sentiment analysis research. In addition, this study extends the usage of sentiment analysis in airline marketing research to the leisure airline context.

The main argument of the study on managerial implications is that a unique study of leisure airline consumers is practical. Among the findings, i) the high negative overall scores, ii) different airlines having different rating score intensities and iii) average and low average scores in different rating categories are relevant to this analysis. On the other hand, the sentiment analysis results of the study can also contribute to sectoral decision-makers. While it is possible to identify general trends through rating scores, with the evaluation of specific sentiments, airline decision-makers can make more effective decisions by interpreting the emotion-specific reactions of consumers.

The study focusing on Airlinequality.com (Skytrax, 2025a) user reviews and employing a transformers-based sentiment analysis approach has limitations on both sample and methodological sides. For the sample side, the study only examines the reviews on the Airlinequality.com website. However, there are several online platforms where users post their reviews and feedback, which can be the possible data sources for future studies. On the other hand, the study examines only the emotional side of the user reviews through sentiment analysis. However, the text side of the reviews can be examined through text mining-based methodologies such as topic modeling to extract topics.

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