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Cost leadership strategies in low-cost airlines: A deep learning-based comparative analysis of Ryanair and Pegasus

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ABSTRACT

Air transportation plays a crucial role in the development of the global tourism industry, facilitating the movement of travellers across different regions and enhancing accessibility to tourism destinations. Airline companies generally operate under traditional, low-cost, non-scheduled, or regional business models. This study focuses on low-cost carriers (LCCs) that implement a cost leadership strategy to maintain competitiveness in the industry. It investigates whether these airlines effectively apply this strategy, identifies their similarities and differences, and evaluates the impact of their cost leadership approach on social media perceptions. A mixed-methods approach was employed, incorporating two key methodologies: (a) document analysis of airline financial reports to assess cost leadership practices and (b) sentiment analysis of customer perceptions using deep learning algorithms, including recurrent neural networks (RNNs), long short-term memory (LSTM), bidirectional LSTM (Bi-LSTM), and gated recurrent units (GRUs). This AI-driven analysis ensured a high degree of classification accuracy in sentiment evaluation. The results indicate that Ryanair strictly adheres to its cost leadership strategy, yet it experiences lower customer satisfaction levels on social media. Conversely, Pegasus Airlines receives higher customer satisfaction ratings, but its cost leadership implementation is less effective. These results highlight the trade-off between operational cost efficiency and the overall tourism experience, offering valuable insights for airline executives, tourism policymakers and industry researchers.

KEYWORDS

cost leadership, low-cost airlines, competitive strategy, sentiment analysis, deep learning

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1. Introduction

The extensive travelling undertaken by individuals to explore diverse countries, uncover novel cultures, and establish business relationships have significantly contributed to the global advancement of tourism (O'Connell, 2018). The swift evolution of air transportation has transformed many nations into accessible hubs, allowing passengers to reach renowned destinations and less familiar places (Belobaba & Odoni, 2009). Over

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the years, the progression of technologies utilised in civil aviation has markedly expedited travel and invigorated the tourism sector (Devlet Hava Meydanları İşletmesi, 2020). Furthermore, the rising availability of economical flights has catalysed the expansion of the travel industry, and this serves as a vital component of the tourism sector (Roney, 2018).

Low-cost airlines, the focus of this research, have played a key role in opening up new destinations like Northern Italy and expanding destination diversity. Similarly, long-haul charter flights have boosted tourism in popular spots including Caribbean Islands, the Maldives and Seychelles (Bieger & Wittmer, 2006). In 2019, global airline revenue surpassed $838 billion, and the passenger count exceeded 4.54 billion (International Air Transport Association [IATA], n.d.b). Analysing figures related to the airline industry reveals its substantial contributions to employment, welfare, trade and tourism in the increasingly global economy (Çelik, 2017).

As a service-intensive industry, the aviation sector demands continuous monitoring of customer expectations. Air travel is primarily chosen for its speed; however, factors such as comfort, safety, connectivity and cost also influence consumer preferences (Morrisson & Winston, 1985). To remain competitive, airlines develop their business models based on market dynamics, positioning themselves strategically within the industry. Airline business models are generally classified into traditional, low-cost, non-scheduled and regional operators (IATA, n.d.a). Each category follows a distinct strategic approach, where Porter's (1980) competitive strategy framework aligns differentiation with traditional airlines, cost leadership with low-cost carriers (LCCs), and focus strategy with regional airlines (Sarılgan, 2019).

Despite the prevalence of cost leadership in LCCs, there is a notable gap in the literature regarding its real-world effectiveness and competitive implications. This study aims to bridge this gap by analyzing two low-cost airlines (Ryanair and Pegasus Airlines) to assess how they implement cost leadership and how their strategic choices influence customer perceptions on social media. The central research problem addressed in this study is to determine the extent to which cost leadership strategies are effectively applied by low-cost airlines and how these strategies shape public perception as expressed on social media.

A mixed-methods approach was adopted, incorporating document analysis of airline financial reports to assess cost leadership implementation, and sentiment analysis of X.com (formerly Twitter) discussions using deep learning algorithms (recurrent neural network [RNN], long short-term memory [LSTM], bidirectional LSTM [BiLSTM], gated recurrent unit [GRU]) to evaluate passenger perceptions.

This study reveals similarities and differences in competitive strategies between Ryanair and Pegasus Airlines, offering insights into how the low-cost airline business model is evolving. Additionally, the application of deep learning algorithms in social sciences remains underutilized. Traditional research methods, such as surveys, dominate social science disciplines, whereas AI-driven sentiment analysis presents a novel approach to analyzing large-scale consumer data. This research, therefore, not only enhances understanding of cost leadership in LCCs but also provides a comprehensive methodological framework for future investigations in the field.

2. Theoretical background

2.1. Airline industry in the tourism sector

The relationship between tourism and the aviation industry has been extensively analyzed in previous studies, consistently demonstrating a strong interdependence (Bieger & Wittmer, 2006; Duval, 2013). As a dynamic sector, air transportation has undergone substantial developments, significantly impacting the global tourism industry. The increasing number of tourists in various regions has led airline operators to expand their networks, adding new airports and destinations (Lohmann & Duval, 2014). Alongside long-haul flights, 'thermal' tourism has emerged as an alternative to traditional winter tourism, contributing to the diversification of international tourism markets (Bieger & Wittmer, 2006).

Low-cost airlines have been able to provide their customers with a quick alternative to other airlines and modes of transportation, often at the expense of reduced service offerings. However, studies have shown that service quality remains a critical determinant of passenger satisfaction, even in the low-cost segment (Kaspar, 1993; Lohman & Duval, 2014; Signorini et al., 2002). Strategically, low-cost airline operators are often more likely than traditional airline operators to focus on regional or secondary airports that were no longer preferred (Costa et al., 2017), and where high-speed trains cannot reach. The development of these destinations has been made possible by offers that attract tourists to these regions, diverse and quality services, as well as collaborative strategies between airlines, local airports, and regional and local authorities (Costa, 2016; Dobruszkes et al., 2016; Tucki et al., 2019).

2.2. Business Model Concept in the Airline Industry

In the airline industry, various business models influence service quality, which in turn creates distinctions among companies. These distinctions impact customer expectations and perceived values. The two predominant models in the sector are traditional (full-service) airlines and low-cost (charter) airlines (Doganis, 2006; Gillen & Gados, 2008). Additionally, regional airlines connect smaller locations to major hubs, contributing to enhanced connectivity (Forbes & Lederman, 2007). The impact of these models on passengers varies significantly. For instance, traditional airlines tend to focus on providing a comfortable journey, whereas low-cost carriers, like Ryanair – the first to introduce low-cost service in Europe – offer shorter flight times and charge extra for additional services, thereby prioritising low ticket prices over service differentiation.

In recent years, the boundary between low-cost and full-service airline models has become increasingly blurred. Pegasus Airlines, for example, offers connecting flights through its hub in Istanbul and operates medium- to long-haul international routes, including destinations in Asia. Although it identifies as a low-cost carrier, Pegasus incorporates features more commonly associated with hybrid or full-service models, such as tiered service packages, loyalty programs and central airport operations. This evolution reflects a broader trend in the industry where airlines adopt mixed strategies to meet diverse customer expectations while maintaining competitive efficiency (Baláž, 2021; Stoenescu & Gheorghe, 2017). This convergence of business models highlights how carriers once classified as strictly low-cost are increasingly incorporating features of full-service airlines, thereby blurring the traditional boundaries between different airline business types (Liubarets et al., 2022; Lohmann & Koo, 2013).

The literature contains extensive research on low-cost airline operators (Brueckner et al., 2013; Chou, 2015; Kos Koklic et al., 2017; Mikulić & Prebežac, 2011). Gillen and Lall (2004) investigated the sources of competitive advantages of low-cost airlines such as EasyJet, Ryanair, and Southwest. They stated that this point-to-point business model provides a strategic advantage, and operational efficiency complements this choice.

Comparative studies on low-cost airline operators show that topics are categorized into areas such as customer loyalty, customer behaviour, competition, business models, tourism, airports, management, frequent flyer programs and pricing. Detailed analyses reveal that competition and business models, along with their influence on tourism and customer loyalty, are the most studied aspects. Generally, low-cost carriers are compared with traditional airlines (Alderighi et al., 2012). When comparing low-cost airlines within their business model framework, studies often focus primarily on pricing. This research compares two low-cost airline operators and is significant for not just examining pricing but also exploring the characteristics of these operators in relation to their cost leadership strategies, similar to previous studies.

2.3. Competitive strategies in airline business models

In order for each business to create a successful competition process in the sector in which it operates, it must establish differences based on strong competition with other businesses. In this way, the target audience can be engaged with the capabilities and approaches of the business that can be perceived differently from other businesses when viewed by customers, making a difference. Porter (1980) divided the general competitive strategies employed by businesses to gain a competitive advantage into three categories: differentiation strategy, cost leadership strategy and focus strategy. The fact that Porter's generic strategies are still relevant in competition during the digital age is also acknowledged in academic research and adapted to the present day (Kim et al., 2004).

Several studies have explored competitive strategies in the airline sector from different perspectives. İbik (2006) highlighted the importance of service quality in the airline sector's competitive landscape, while Karasu (2007) examined the advantages that low-cost airlines possess on long-haul routes. Tunç (2007) compared the competitiveness of Turkish airlines with European counterparts during negotiations, whereas Aldemir and Kuyucak Şengür (2018) explored competition strategies among Turkish airlines. Erdoğan (2014) discussed regulatory and competitive strategies influenced by liberalization, and Saldıraner (2016) proposed a strategic model for low-cost airlines in Turkey. Tanrıverdi and Küçükyılmaz (2018) analysed the collaborative competition strategies of traditional airlines, and Yaşar (2020) investigated market strategies affecting passenger purchasing behaviour in Turkey's domestic market. Additionally, Karabulak (2016) contrasted traditional and low-cost airlines, while Şenel (2018) addressed the role of human resource management in providing sustainable competitive advantages for air cargo companies. Finally, Aldemir (2018) and Şimşek (2018) evaluated competitive strategies within the Turkish airline industry, alongside Hopalı (2016), who conducted a competitiveness analysis in aviation.

The existing literature highlights the importance of strategic differentiation and cost efficiency in maintaining long-term competitiveness in the airline industry. This study builds on previous research by investigating how cost leadership strategies influence both airline operations and consumer perceptions, using deep learning-based sentiment analysis to provide data-driven insights.

3. Methodology

This study used a mixed-methods technique to examine low-cost airlines' cost leadership strategies. Data was collected using two primary methods. First, airline company reports were studied using the document analysis approach, with a focus on the operational and strategic characteristics of airlines that follow a cost leadership strategy. The document analysis included publicly available annual reports, investor presentations and official press releases published on the corporate websites of Pegasus Airlines and Ryanair. These documents provided insights into pricing strategies, operational performance, ancillary revenue streams and service models between 2020 and 2025. This approach made it possible to thoroughly assess how airlines incorporate cost leadership concepts into their business plans. Second, the deep learning method was applied to perform sentiment analysis on data obtained from X.com, a widely used social media platform. This phase aimed to assess customer perceptions regarding cost leadership features implemented by airlines. The data collected consisted of secondary data accessed on X.com. Sentiment analysis was conducted to determine public perceptions towards the cost leadership strategy and to classify the sentiments with high accuracy using deep learning algorithms including RNNs, LSTM, BiLSTM and GRUs.

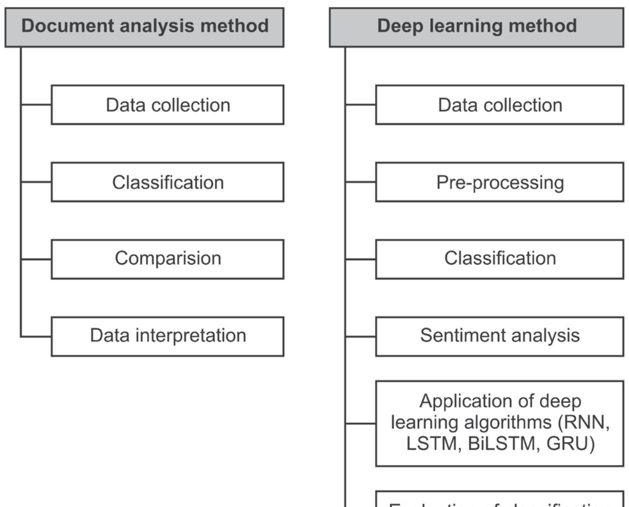

Figure 1. Research process
Note: RNN – recurrent neural network, LSTM – long short-term memory, BiLSTM – bidirectional neural network, GRU – gated recurrent unit
Source: authors

The research process consisted of several phases, as shown in Figure 1. In the document analysis method, the phases included data collection, classification, comparison and interpretation. In the deep learning method, the phases included data collection, preprocessing, classification, sentiment analysis, algorithm application and classification evaluation. This combination of methods ensured a robust analysis of both operational reports and customer sentiments, providing a holistic view of cost leadership strategy implementation in the airline industry.

3.1. Research sample

3.1.1. Ryanair

Ryanair has modelled its operations on Southwest Airlines, establishing itself as Europe's first low-fare airline. Today, it is the continent's largest airline group, operating Ryanair, Buzz, Lauda and Malta Air. As of 2025, it has managed a fleet of over 600 aircraft and serves more than 230 destinations across 40 countries, with approximately 2,600 daily flights (Flightradar24, n.d.; Ryanair, n.d.a, n.d.b; Tran et al., 2015). The company continues to prioritize punctuality and cost-efficiency, maintaining a high on-time performance and focusing on secondary airports and ancillary revenues to sustain its cost leadership strategy (Ryanair Group, 2025).

3.1.2. Pegasus

Pegasus Airlines, established in 1990 in Istanbul, began operations as a joint venture with Aer Lingus. After being acquired by ESAS Holding in 2005, it transitioned into a scheduled low-cost airline. Emphasizing affordable travel with its slogan "everyone has the right to fly", Pegasus has grown steadily. As of 2025, it operates flights to over 130 destinations in 50 countries, including more than 40 domestic and 90 international routes, with a modern Airbus-dominated fleet (CAPA, n.d.; Pegasus Airlines, n.d.).

3.2. Data evaluation tools

3.2.1. Document analysis

This study assessed airline strategies related to cost leadership by analyzing textual data from corporate reports published between 2020 and 2025. These documents offered valuable insights into pricing models, operational efficiency, ancillary revenue structures and overall service strategies. The data were categorized and interpreted in accordance with the cost leadership framework. Subsequently, sentiment analysis results for both Ryanair and Pegasus were incorporated to provide a comparative evaluation. This dual approach enabled a comprehensive understanding of how low-cost carriers implement and communicate their cost leadership strategies.

3.2.2. Sentiment analysis

Sentiment analysis was utilized to analyze and interpret information from X.com. The platform's 'character cap' and the presence of slang, emojis and abbreviations created difficulties. Natural language processing methods were used in conjunction with machine learning and deep learning algorithms to categorize text and extract insights (Poria et al., 2015).

3.2.2.1. Deep learning algorithms (RNN, LSTM, BiLSTM, GRU)

The study employed sophisticated deep learning algorithms to categorize and evaluate textual data. These algorithms featured RNNs, which are particularly effective at recognizing patterns within sequential information, alongside LSTMs and GRUs, which tackle long-term dependency issues in data analysis (Abdalrahman, 2020; Hochreiter & Schmidhuber, 1997). Every algorithm presents distinct benefits:

1. RNNs: Suitable for sequential tasks such as sentiment analysis and speech recognition.
2. LSTMs: Address challenges such as vanishing gradients, rendering them suitable for long-term memory tasks.
3. BiLSTMs: Utilize both forward and backward passes of sequential data to improve prediction accuracy.
4. GRUs: Simplify training for small datasets and enhance memory capacity by incorporating reset and update gates.

The effectiveness of these algorithms was assessed utilizing metrics like accuracy, precision, recall and F_1 score (Figure 2). These metrics offered a thorough evaluation of the model's classification performance.

	(Predicted)	
(Actual)	True positives (TP)	False negatives (FN)
	False positives (PN)	True negatives (TN)

Figure 2. Confusion matrix
Source: authors

Accuracy: employed to assess the effectiveness of a model. The ratio of the data that is correctly estimated in the model to the total data set is calculated with the accuracy value.

$$\frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{FP}+\mathrm{TN}+\mathrm{FN}}$$

Precision: shows how many of the values predicted as positive are actually positive.

$$\text{Precision} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}$$

Recall: a metric that shows how many of the transactions that should be predicted as positive are predicted as positive.

$$\text{Recall} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}$$

F_1 score: shows the harmonic mean of precision and recall values.

$$F_1 = 2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}}$$

3.3. Data compilation process

3.3.3. Data collection

Data were collected from X.com via API, with Pegasus and Ryanair's official accounts tagged for weekly tweet retrieval. Between March 14, 2021, and September 13, 2021, a total of 26,771 tweets related to Pegasus and 126,667 tweets related to Ryanair were gathered. Although the number of tweets analyzed for Ryanair was significantly higher than that for Pegasus, data normalization techniques were applied to ensure consistency in sentiment classification. The results are interpreted comparatively, considering the proportional frequency of sentiment types rather than absolute counts to minimize skewness due to dataset imbalance.

3.3.4. Pre-processing

The pre-processing stage involved cleaning raw data to improve model efficiency. Unnecessary elements, such as punctuation, URLs, hashtags, HTML tags and meaningless stop words were removed. Text was standardized by converting all letters to lower case. The most frequently used words in Ryanair's tweets included "flight", "refund" and "book", while Pegasus-related tweets commonly featured "ticket", "inform" and "time" (Figures 3 and 4).

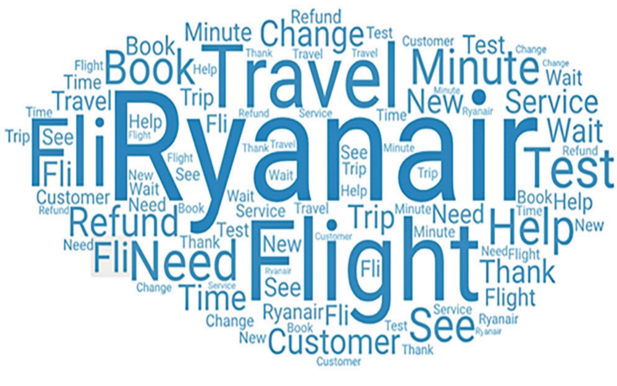

Figure 3. Most used words in Ryanair data set
Source: authors

Figure 4. Most used words in Pegasus data set
Source: authors

In the preprocessing stage, similar words and phrases were grouped using tokenization and lemmatization techniques. The tag clouds presented in the study were generated based on frequency of lemmas, after removing stopwords and normalizing variations in spelling and tense to reflect dominant themes accurately.

3.3.5. Classification

Classification was conducted using Python-based tools, including NLTK and Gensim, for natural language processing. Data were categorized based on cost leadership characteristics, such as price, booking methods, airport usage and customer service (O'Connell & Williams, 2005). Ryanair's tweets predominantly referenced in-cabin services (31%), airport operations (30.7%) and wait/cancellation issues (24.4%). For Pegasus, the majority of tweets related to wait/cancellation (34.98%), in-cabin services (25%) and airport operations (23.7%) (Table 1).

4. Findings

4.1. Document analysis results

The analysis examined various characteristics associated with the implementation of cost leadership strategies in low-cost airlines. These characteristics include sub-brands, which represent additional operations under the primary airline, and ticket pricing, which reflects the core of the low-cost model by offering competitive fares. The study also evaluated distribution channels, focusing on methods like online reservations and direct bookings, as well as airport usage which emphasizes the preference for secondary or regional airports to reduce operational costs. Additionally, connections (transfers) were analyzed to understand how airlines manage flight links and optimize passenger flow. The

Table 1. Data classification based on cost leadership strategy characteristics

Category	Classification	Ryanair		Pegasus	
		No. of tweets	%	No. of tweets	%
Brand	Brand	4,190	3.3	1,006	3.7
Ticket pricing	Price	5,735	4.4	2,272	8.4
Distribution	Booking/online	8,962	7.0	3,594	13.3
Airport usage	Airport	38,980	30.7	6,355	23.7
Connections	Transfer	7,825	6.1	1,969	7.3
Class offerings	Class	1,642	1.2	2,072	7.7
In-cabin services	Crew/food/luggage	39,604	31.2	6,461	25.0
Aircraft utilization	Frequent	648,000	0.5	107,000	0.3
Ground wait times	Wait/cancellation	30,992	24.4	9,437	35.1
Product quality	Quality	4,821	3.8	927,000	3.4
Ancillary revenues	Fee	8,411	6.6	2,072	7.7
Aircraft type	Boeing/Airbus	21,613	17.0	5,877	21.9
Seating and comfort	Seat/comfort	7,314	5.7	5,049	18.7
Customer service	Customer	10,616	8.3	2,195	8.1
Operations	Transport	4,118	3.2	1,549	5.7

Source: authors.

number of classes offered on flights was considered, revealing the streamlined approach of low-cost carriers to cabin configurations (Table 2).

Furthermore, in-cabin services, such as crew, food, and luggage management, were assessed as part of the cost control strategies. The evaluation extended to aircraft utilization rates, which are critical for maximizing operational efficiency and minimizing idle time. Waiting time on the ground was another important metric, highlighting the airlines' ability to minimize delays and cancellations to enhance operational reliability. Secondary revenues, derived from ancillary services such as baggage fees and seat selection, were also a key area of focus. The analysis included customer service, which reflects passenger satisfaction and service quality, and operational

Table 2. Ryanair and Pegasus' competitive strategy practices

Category	Classification	Ryanair (no. of tweets, %)
Mission	"We believe that everyone has the right to travel by air. The Pegasus Family, our suppliers and our business partners are all working together to achieve this"	"We are offering low fares that will drive increased passenger traffic, while continuing to focus on limiting costs and efficient operations"
Sub-brands	–	Buzz, Lauda, Malta Air, Ryanair
Ticket price	Pegasus promotes affordable flights, offering additional services (e.g. seat selection, meal selection) for extra charges. Passengers can customize their experience based on their preferences	Ryanair's low fares are designed to stimulate demand, especially among budget-conscious travelers. Fares are adjusted based on demand and proximity to departure dates. Promotional campaigns are periodically introduced
Distribution	Tickets are sold via Pegasus' website, mobile app, and through commission-based agencies with enhanced integration systems for faster booking	Ryanair's reservations are primarily managed through the Ryanair.com website and mobile app. Real-time booking and payment are supported by a reservation system developed by Navitaire
Links	Pegasus focuses on short and medium-haul flights, covering 113 destinations in 43 countries, including 35 domestic and 78 international routes	Ryanair operates point-to-point short-haul flights, covering 88 destinations in 40 countries. It eliminates extra services such as transit baggage handling and transfer passenger support to reduce costs
Number of classes	Economy class only, with four flight packages: Super Eco, Eco, Advantageous, and Flexible Packages	Economy class only, with three flight packages: Plus, Family Plus, and Flexi Plus
In-cabin services	All services, except cabin baggage, are chargeable	All services, except cabin baggage, are chargeable
Aircraft utilization rate	An average of 9 hours per day	An average of 9 hours per day
Waiting time on the ground	Approximately 87% as of March 2024	Approximately 96% in 2024
Airport usage	Operates in secondary airports in Europe (e.g. Brussels South Charleroi, Marseille, Berlin Schoenfeld)	Operates in secondary airports in Europe (e.g. Brussels South Charleroi, Bordeaux, Liverpool, London Luton)
Secondary revenues	Ancillary revenues ~30% of total revenue in 2023 (~€810 m), covering seat selection, baggage, meals, etc.	Ancillary revenues ~35.7% in FY 2023 (€3.845 bn), from inflight sales, seat upgrades, baggage fees etc.
Aircraft	Fleet includes 118 aircraft, primarily Airbus A320-200 CEO/NEO and A321 NEO, plus 9 Boeing 737-800 (average fleet age: 4.6 years)	Fleet includes approximately 619 Boeing 737s, including 410 B737-800 and 157 B737 MAX 8/8200
Seats	Seat pitch: B737-800 (73.66 cm), A320 (71.12 cm). Emergency exit seats: 83.82 cm to 101.6 cm	Seat width: 43.2 cm; seat depth: 58 cm; seat pitch: 76.2 cm
Customer service	Includes Travel Assistant (mobile app), WhatsApp support, website help, and phone services	Daily calls with airport staff to address delays and baggage issues. Live Chat, phone support, and online surveys are used to measure satisfaction
Operational activities	Focused solely on transportation services	Focused solely on transportation services

Source: Boeing (n.d.), CAPA – Centre for Aviation (n.d.), Pegasus Investor Relations (n.d.a., n.d.b), Planespotters.net (n.d.), Ryanair Group (2024).

activities, which encompass the airlines' overall performance in delivering cost-effective and efficient services. These combined characteristics provide a comprehensive view of how low-cost carriers implement cost leadership strategies to maintain competitiveness in the airline industry.

4.2. Sentiment analysis results

The sentiment analysis results provide key insights into customer perceptions regarding the cost leadership strategies implemented by Ryanair and Pegasus Airlines. Following the pre-processing stage, sentiment analysis was conducted using TextBlob, which categorized tweets into positive (polarity > 0), neutral (polarity = 0) and negative (polarity < 0) classifications.

For Ryanair, the analysis revealed that 32.07% of tweets were classified as positive, 53.24% as neutral and 14.67% as negative. Among all categories, airport operations received the highest proportion of positive mentions, followed by crew, luggage, food, wait and cancellation. Conversely, the in-cabin service category (crew, luggage, food) had the highest share of negative sentiment, indicating customer dissatisfaction with service quality and ancillary charges. Additionally, while price, customer service and comfort were positively perceived, cancellations and waiting times led to significant negative feedback, suggesting operational challenges in these areas.

Similarly, for Pegasus Airlines, 35.53% of tweets were positive, 50.30% were neutral, and 14.15% were negative. The wait and cancellation category were the most positively rated, followed by airport operations and in-cabin services (crew, luggage, food). However, the same category also had the highest percentage of negative tweets, reflecting mixed passenger sentiments regarding delays and cancellations. Further analysis indicated that price, online bookings, customer service and operational activities were generally well-received by Pegasus customers, contributing to a favourable brand image.

A detailed breakdown of sentiment distribution for various service categories is provided in Table 3,

Table 3. Sentiment analysis results for Ryanair and Pegasus Airlines

Class	Ryanair negative (%)	Ryanair neutral (%)	Ryanair positive (%)	Pegasus negative (%)	Pegasus neutral (%)	Pegasus positive (%)
Brand	26.2	34.9	38.9	13.4	52.9	33.8
Price	20.1	34.4	45.5	19.7	38.9	41.4
Online	20.6	41.6	37.8	12.0	46.6	41.4
Booking	17.0	40.2	42.8	13.3	39.9	47.8
Airport	17.0	47.0	36.0	18.1	40.0	41.9
Transfer	19.3	43.6	37.1	19.3	37.7	43.9
Class	23.5	31.2	45.3	19.7	35.4	44.9
Crew	16.6	48.8	34.6	15.0	36.8	48.2
Luggage	17.4	43.9	38.7	18.7	37.7	43.6
Food	20.9	39.6	39.5	12.5	50.7	36.8
Frequent	21.8	33.2	45.1	21.5	33.6	44.9
Wait	18.6	37.4	44.0	16.3	39.8	43.9
Cancellation	20.9	43.4	35.8	14.5	48.3	37.1
Quality	7.7	6.2	86.0	20.2	10.9	68.9
Fee	19.5	41.2	39.4	18.1	39.9	42.0
Airbus	14.6	56.5	28.8	17.2	36.0	46.8
Boeing	15.1	54.7	30.2	16.6	34.5	49.9
Seat	16.8	39.6	43.6	18.2	43.6	38.3
Comfort	10.7	36.7	52.6	16.3	41.2	42.5
Customer	20.1	36.8	43.1	14.3	38.9	46.9
Transport	21.4	38.0	40.6	19.6	34.9	45.6

Source: authors.

illustrating the percentage of positive, neutral, and negative tweets for each classification. The results show that both airlines perform well in some areas while experiencing severe consumer dissatisfaction in others.

Tweet analyses provided insights beyond just aggregated sentiment. A negative Pegasus tweet cited airport operations, in-cabin services and Boeing/ Airbus issues, expressing frustration with flight delays. A Ryanair tweet on cancellations and customer service was flagged, showing customer dissatisfaction with operations but one about customer service and cancellations received positive feedback for quick responses and accessible care. Although both airlines have a strong brand presence, the sentiment research results indicate that they face customer discontent in operational areas like cancellations and delays. However, Pegasus Airlines has a marginally stronger public image in terms of comfort and customer service, whereas Ryanair's cost-cutting efforts, including greater luggage costs, seem to contribute to higher negative attitude.

4.3. Deep learning analysis results

Recurrent neural network (RNN), bidirectional long short-term memory (BiLSTM), gated recurrent unit (GRU) and long short-term memory (LSTM) models are used to illustrate the dataset's results in this part. To achieve optimal model performance, the pre-processed tweets were separated into training, validation and testing datasets.

The deep learning models were first trained and tested on the Ryanair dataset. The dataset from Pegasus Airlines was then classified using the most successful model, which was used to confirm the classification. A total of 70% of the dataset was devoted to the training set, with 30% going to each of the validation and testing sets. When validation performance deteriorated, training was stopped using an earlystopping method to avoid overfitting.

The effectiveness of the deep learning models that were used was assessed using important classification measures, such as F_1 score, accuracy, recall and precision. Root mean square propagation (RMSprop) was used as the optimizer, sigmoid as the activation function, and binary cross-entropy as the loss function in order to optimize the models. The batch size was set at 128 and the number of epochs was set at 10. Because too many training cycles could result in overfitting, the epochs were chosen to balance training effectiveness and model generalization.

A loss score near 0 is indicative of a high-performing model. All models were tested for accuracy, precision, recall and F_1 scores, with scores close to 1 indicating high success (Alharbi & de Doncker, 2018).

4.4. Comparison of deep learning models

The results obtained from RNN, LSTM, GRU and BiLSTM) models are presented in Table 4. The analysis indicates that the RNN model exhibited relatively lower performance across all metrics. The LSTM model outperformed all other models, achieving the highest performance in almost all metrics, with an accuracy rate of 90%. The GRU model also performed well, demonstrating high sensitivity (recall) with a score of 0.89.

Table 4. Results of deep learning algorithms

Deep learning algorithms	Loss	Accuracy	Precision	Recall	F_1 score
RNN	0.08	0.83	0.87	0.81	0.84
LSTM	0.04	0.90	0.94	0.88	0.91
GRU	0.05	0.90	0.92	0.89	0.90
BiLSTM	0.06	0.87	0.88	0.87	0.87

Note: RNN – recurrent neural network, LSTM – long short-term memory, GRU – gated recurrent unit, BiLSTM – bidirectional neural network.

Source: authors.

The training and validation loss curves, presented in Figures 2 and 3, indicate that while the loss decreased progressively during training, overfitting was detected after 10 epochs, leading to the decision to limit training cycles.

Accuracy curves of all deep learning models show that LSTM achieved the highest accuracy, while RNN exhibited the lowest verification rate. Loss curves indicate that LSTM had the lowest loss score, whereas RNN had the highest loss score (Figures 5 and 6).

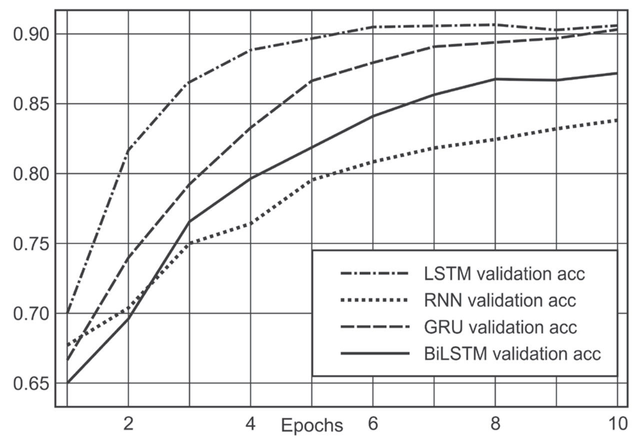

Figure 5. Deep learning algorithm accuracy curves
Note: RNN – recurrent neural network, LSTM – long short-term memory, GRU – gated recurrent unit, BiLSTM – bidirectional neural network
Source: authors

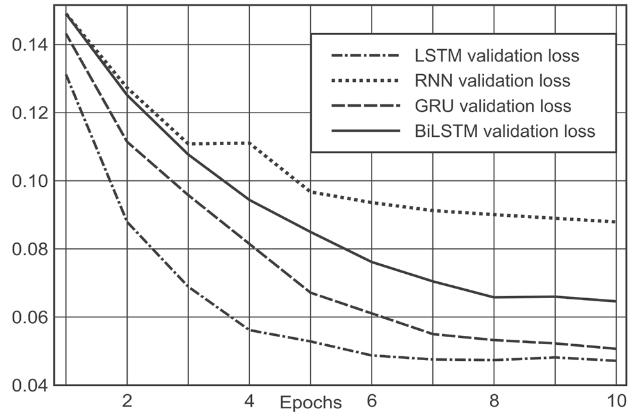

Figure 6. Deep learning algorithm loss curves
Note: RNN – recurrent neural network, LSTM – long short-term memory, GRU – gated recurrent unit, BiLSTM – bidirectional neural network
Source: authors

The RNN model exhibited lower performance compared to other models. While its accuracy improved from 0.49 in the first cycle to 0.89 in the tenth cycle, the validation accuracy only reached 0.83. The training loss decreased from 0.20 to 0.02, while the validation loss declined from 0.14 to 0.08 (Figures 7 and 8).

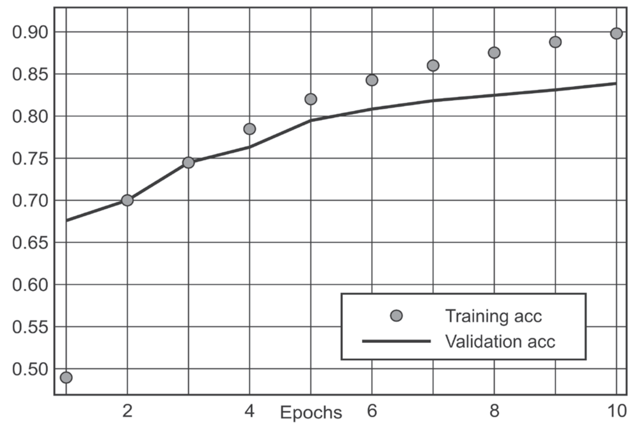

Figure 7. Recurrent neural network (RNN) accuracy curves
Source: authors

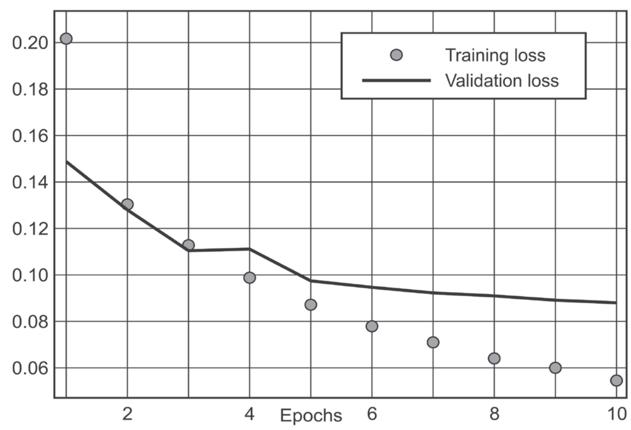

Figure 8. Recurrent neural network (RNN) loss curves
Source: authors

The GRU model showed significant improvements, achieving 93% training accuracy by the tenth cycle and a validation accuracy of 90%. The training loss dropped from 0.20 to 0.03, while validation loss decreased from 0.14 to 0.05 (Figures 9 and 10).

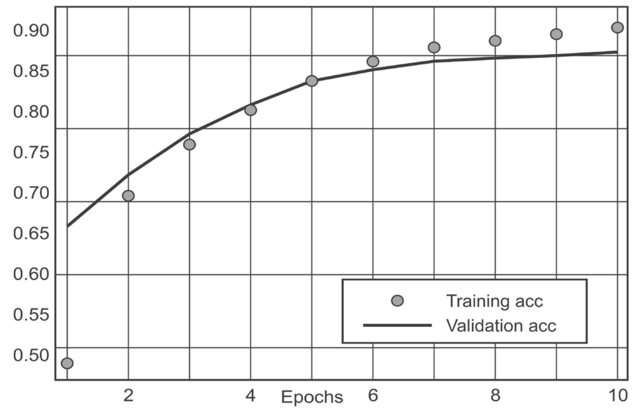

Figure 9. Gated recurrent unit (GRU) accuracy curves
Source: authors

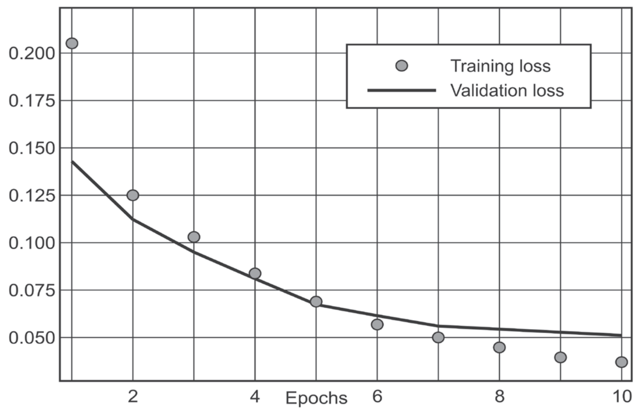

Figure 10. Gated recurrent unit (GRU) loss curves
Source: authors

The LSTM model achieved the highest overall accuracy (94%) with an F_1 score of 0.91. The training loss dropped significantly from 0.20 to 0.02, and the validation loss was reduced from 0.13 to 0.04 (Figures 11 and 12).

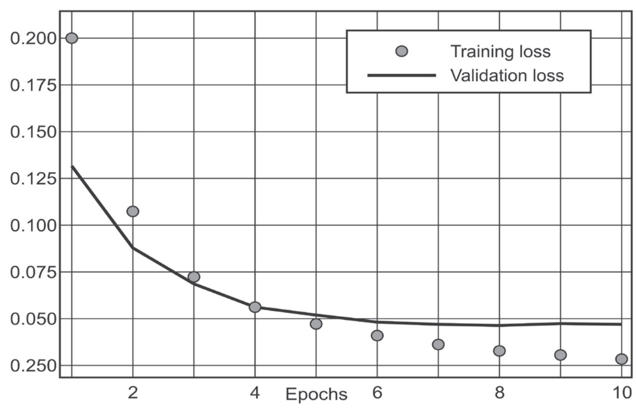

Figure 11. Long short-term memory (LSTM) accuracy curves
Source: authors

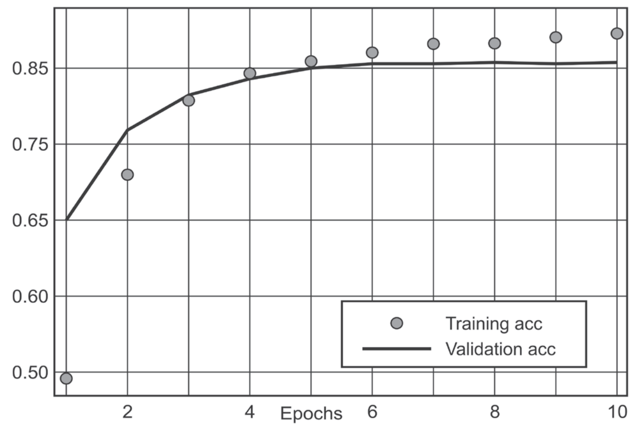

Figure 12. Long short-term memory (LSTM) loss curves
Source: authors

The BiLSTM model performed slightly lower than the LSTM and GRU models, with an accuracy of 87% and an F_1 score of 0.87. The training accuracy improved from 0.50 to 0.90, while validation accuracy increased from 0.64 to 0.87. The training loss decreased from 0.19 to 0.04, and the validation loss dropped from 0.14 to 0.06 (Figures 13 and 14).

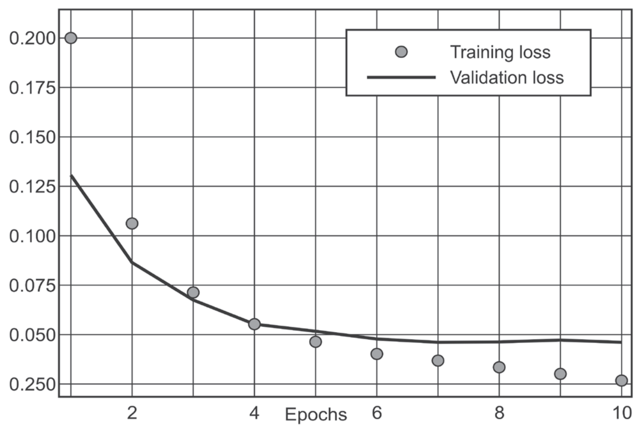

Figure 13. Bidirectional neural network (BiLSTM) accuracy curves
Source: authors

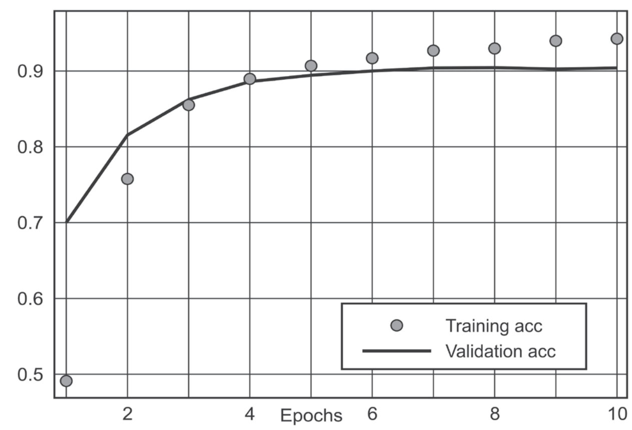

Figure 14. Bidirectional neural network (BiLSTM) loss curves
Source: authors

4.5. Evaluation of classification results

The classification results from the deep learning models were evaluated within the framework of the cost leadership strategy characteristics. The precision, recall (sensitivity), and F_1 score for each category were analyzed using RNN, LSTM, GRU and BiLSTM.

4.5.1. Performance analysis of key classifications

For the brand category, LSTM and GRU achieved 96% precision, 87% recall and an F_1 score of 91%, making LSTM the most effective model. Similarly, price classification had 97% precision and 96% recall, confirming LSTM's strong performance (Table 5).

Table 5. Evaluation of tweets belonging to classifications

Category	Model	Precision	Recall	F_1 score
Brand	LSTM	0.96	0.87	0.91
Price	LSTM	0.97	0.96	0.97
Online	GRU	1.00	0.97	0.98
Booking	LSTM	0.77	0.83	0.80
Airport	LSTM	1.00	1.00	0.99
Transfer	GRU	0.98	0.96	0.97
Class	LSTM	0.63	0.46	0.53
Crew	LSTM	1.00	1.00	1.00
Luggage	GRU	0.97	0.95	0.96
Food	RNN	1.00	0.14	0.25
Frequent	GRU	0.99	0.65	0.77
Wait	LSTM	0.90	0.76	0.82
Cancellation	GRU	0.98	0.99	0.99
Quality	LSTM	0.99	0.97	0.98
Fee	GRU	0.99	0.99	0.99
Airbus	LSTM	0.98	0.97	0.96
Boeing	LSTM	0.97	0.97	0.97
Seat	LSTM	0.97	0.85	0.91
Comfort	LSTM	0.99	0.96	0.98

Note: LSTM – long short-term memory, GRU – gated recurrent unit, RNN – recurrent neural network.
Source: authors.

In the distribution category, GRU achieved 100% precision in online booking classification, while LSTM performed best in standard bookings (80% F_1 score). Airport-related tweets were classified with 100% precision and recall using the LSTM model, confirming high accuracy in this category.

For transfer classification, GRU performed best with 98% precision, 96% recall and an F_1 score of 97%. Meanwhile, flight class classification showed lower accuracy, with LSTM achieving 63% precision and 46% recall, indicating a more complex classification process.

In the in-cabin services category, crew classification was highly accurate across all models, reaching 100% precision and recall. Luggage classification was most effective with 97% precision and 95% recall (GRU model), while food classification had 100% precision with RNN but lower recall (84% with GRU model).

For aircraft utilization rate (frequent), GRU achieved the highest precision (99%), but recall was lower (65% with LSTM). The waiting and cancellation classifications had high accuracy, with LSTM achieving 90% precision for wait and 99% precision for cancellations (GRU model).

These findings indicate that LSTM and GRU models were he most effective at classifying tweets related to cost leadership characteristics. The airport, price, and crew categories were classified with high precision, while the class and frequent categories showed lower accuracy due to the complexity of classifications.

4.6. Data evaluation process

4.6.1. Classifying based on document and sentiment analysis results

The mission statements of both airlines reveal their emphasis on cost and pricing strategies, aligning with the cost leadership approach. Pegasus focuses on accessibility, stating, "We believe that everyone has the right to air travel", while Ryanair explicitly connects its mission to its cost leadership model, declaring, "Continue to focus on limiting costs … to offer low fares". This clarity in Ryanair's mission aligns directly with its business model, whereas Pegasus takes a broader approach.

In terms of branding, Pegasus operates as a single brand, while Ryanair benefits from being part of a larger group that includes Buzz, Lauda and Malta Air. Sentiment analysis showed that Ryanair's users have a positive perception of its brand, likely influenced by its group identity, while Pegasus was perceived neutrally. This suggests that Ryanair's brand positioning within its group may enhance its user appeal despite not strictly adhering to cost leadership strategies. Another important dimension is the organizational and legal form of the airlines. Ryanair operates as part of a holding group (including Buzz, Lauda and Malta Air) and this allows economies of scale and strategic diversification (Castro & Lohmann, 2014). Moreover, Ryanair's standardized fleet of Boeing 737s significantly contributes to maintenance and training cost reductions, reinforcing its cost leadership strategy. In contrast, Pegasus operates a mixed fleet which, while offering flexibility, may lead to relatively higher operational costs.

Pricing, a critical element in the cost leadership strategy, was positively perceived for both airlines. Pegasus emphasizes affordable pricing with optional services to enhance comfort, while Ryanair highlights its promotional campaigns and transparent pricing models. These pricing strategies resonate well with users, as reflected in the positive sentiment analysis for both operators.

In distribution, Ryanair uses its proprietary online reservation system (Navitaire), adhering to a strict cost leadership approach, whereas Pegasus relies on agency collaborations that incur additional costs. Despite this deviation, Pegasus received positive sentiment for its distribution system, indicating that customers value the convenience it offers, while Ryanair's feedback remained neutral.

For airport usage, Ryanair serves a greater number of secondary airports compared to Pegasus, aligning with cost-reduction strategies. However, this approach impacts customer satisfaction negatively, as Ryanair received neutral sentiment, whereas Pegasus was viewed positively. Secondary airports often require passengers to travel further, reducing convenience and satisfaction.

In terms of route networks, Pegasus operates in more destinations (124 in 47 countries) compared to Ryanair (88 in 40 countries). This larger network aligns with Pegasus's emphasis on accessibility, contributing to a positive perception among users. In contrast, Ryanair received neutral feedback in this category, despite its focus on frequent point-to-point short-haul flights.

Both airlines offer economy-class only services, with options to upgrade through flight packages. Users perceive these offerings positively, reflecting the appeal of affordable travel options combined with customization possibilities. This reinforces the effectiveness of their cost leadership models in meeting customer expectations.

In-cabin services, such as meals, baggage and cabin crew, are chargeable for both airlines, consistent with their cost leadership strategies. However, Pegasus received positive sentiment for these services, while Ryanair's sentiment was neutral. The difference may stem from variations in service quality, pricing or the overall user experience.

Aircraft utilization rates are crucial for low-cost operators. Ryanair operates at 9.11 hours per day, outperforming Pegasus's 6.2 hours. Sentiment analysis for both airlines was positive, indicating that frequent flights enhance customer satisfaction.

Regarding on-time performance, Ryanair reported a 96% on-time departure rate, compared to Pegasus's 88.4%. Despite this difference, sentiment analysis for both airlines was positive, suggesting that passengers are generally satisfied with their operational efficiency.

Low-cost airlines often simplify their services, providing only the essentials, such as a seat for passengers. This approach received positive sentiment for both airlines, indicating that their streamlined offerings meet passenger expectations.

Secondary revenue streams, including add-ons like seat selection, baggage fees and travel services, account for 37% of Ryanair's revenue and 31% for Pegasus. While Ryanair generates higher ancillary revenue, its sentiment analysis was neutral, suggesting dissatisfaction with additional charges. In contrast, Pegasus's positive sentiment reflects greater acceptance of its optional services.

Fleet uniformity is another key cost-saving measure. Ryanair exclusively operates Boeing 737-800s, while Pegasus uses a mix of Boeing and Airbus models. Surprisingly, Pegasus's diverse fleet received higher customer satisfaction, as reflected in the sentiment analysis.

Lastly, customer service, often limited in low-cost airlines, is handled through various digital and traditional channels by both operators. Pegasus received higher satisfaction ratings due to tools like its Travel Assistant app and WhatsApp support, while Ryanair's sentiment was positive but included a higher proportion of negative tweets. The accessibility and responsiveness of digital tools appear to play a significant role in customer perceptions.

Both airlines focus exclusively on transportation services as part of their low-cost models. This aligns with customer expectations, as evidenced by the positive sentiment in this area. These findings demonstrate how specific elements of the cost leadership strategy impact user perceptions, with some deviations yielding mixed results.

5. Discussion and conclusion

The research analyzed low-cost airline companies within the framework of the cost leadership competition strategy. It utilized document analysis to examine the strategies and practices of Ryanair and Pegasus, as well as sentiment analysis using deep learning methods on user-generated data from the social media platform X.com. The findings revealed how cost leadership features influence customer perceptions and satisfaction.

This study is subject to several limitations. First, the document analysis was based on publicly available corporate reports and investor materials, which may not fully reflect internal strategic decisions. Second, the sentiment analysis relied solely on data from X.com, which may not represent the entire customer base due to demographic and usage biases. Additionally, deep learning models, while powerful, can produce classification errors if trained on imbalanced or noisy data. Finally, the data were collected within a specific time frame (March–September 2021), and therefore the findings may not be generalizable to other time periods. These limitations should be considered when interpreting the findings.

5.1. Key findings

The classification of data based on cost leadership strategy characteristics highlighted significant differences between Ryanair and Pegasus. The most discussed topic for Ryanair was related to airports, while for Pegasus, it was waiting time on the ground. For Ryanair, user perception of airports was neutral, indicating dissatisfaction with the use of secondary and less accessible airports – a common cost-cutting strategy in the low-cost airline model. On the other hand, Pegasus received positive sentiment for waiting time, though negative tweets revealed that passengers still expressed dissatisfaction with delayed or cancelled flights.

Sentiment analysis showed that Ryanair implemented the cost leadership strategy more effectively, particularly in areas such as pricing, point-to-point transportation, and aircraft utilization rates. However, the overall satisfaction level was lower, particularly in categories like in-cabin services, seat comfort, secondary revenues and airport accessibility. These findings suggest that Ryanair's strict adherence to cost leadership principles may lead to dissatisfaction in areas where customers expect higher service quality. Moreover, regional differences between the European Union (EU) and Türkiye play a critical role in shaping cost leadership strategies and passenger expectations. While Ryanair operates within the highly liberalized EU market, benefiting from uniform regulatory frameworks and extensive low-cost travel culture, Pegasus must navigate a more complex regulatory and infrastructural landscape in Türkiye. These contextual factors may influence both the implementation of cost strategies and consumer perceptions across regions.

In contrast, Pegasus demonstrated higher satisfaction rates in categories like seat comfort, in-cabin services, secondary revenues and airport usage. However, this satisfaction indicates a partial deviation from the strict cost leadership strategy. Pegasus aligns more closely with the hybrid airline model, blending features of low-cost and traditional business models. Although Pegasus defines itself as a low-cost carrier, its operational practices increasingly reflect characteristics of a hybrid model. These include offering tiered service packages, using primary airports, and implementing customer service tools that go beyond basic low-cost operations. This divergence between declared strategy and actual practice reveals a shift toward balancing cost efficiency with service quality, especially in response to customer expectations in the Turkish market.

Another important dimension concerns the spatial configuration of the route networks of the two airlines. Ryanair's route map is heavily concentrated within Western and Central Europe, with most destinations clustered in EU countries and a limited reach beyond the region. This model supports short-haul, intra-European tourism. Conversely, Pegasus Airlines, through its hub in Istanbul, operates a wider geographic network, covering not only European destinations but also cities in the Middle East, Central Asia and South Asia. This east-west connectivity reflects Türkiye's unique geostrategic position and plays a significant role in facilitating transregional tourism flows. The contrast in their spatial footprints reveals differing market focuses and opportunities for tourism development aligned with geographical expansion (CAPA, n.d.; Flightradar24, n.d.; Pegasus Investor Relations, n.d.a.; Ryanair Group, 2024).

5.2. Competitive strategies and implications

Ryanair's competitive approach aligns closely with the ultra-low-cost airline model observed in carriers like Spirit, Frontier and Wizz Air. These airlines adopt an aggressive pricing policy, charging for all additional services, such as seat selection, baggage and onboard refreshments. Ryanair's high aircraft utilization rate and limited amenities align with this model, although differences remain in its implementation of some cost-reduction strategies (Bachwich & Wittman, 2017).

Pegasus, on the other hand, appears to have adopted a hybrid model. This strategy emerged post-2008 economic crisis and combines elements of both low-cost and traditional airline models. Features like in-flight entertainment, more diverse fleet structures, and a focus on central airports illustrate Pegasus's approach. While this model enhances customer satisfaction, it deviates from the core principles of cost leadership.

5.3. Conclusions and future directions

The study demonstrates that while Ryanair adheres strictly to the cost leadership strategy, it often sacrifices customer satisfaction in areas where users expect better service. Pegasus, despite defining itself as a low-cost airline, incorporates elements of a hybrid model that cater to customer preferences but dilute the cost leadership approach. These findings suggest that customer awareness and expectations regarding low-cost airline business models play a critical role in shaping satisfaction levels.

For future research, understanding passenger awareness and perceptions of the low-cost airline business model will be critical. Educating customers on the trade-offs involved – such as the benefits of lower fares when using secondary airports – may help align expectations with operational realities. Additionally, further studies could explore how hybrid models can balance cost efficiency with enhanced customer satisfaction, providing a blueprint for airlines seeking to compete in this dynamic industry.

In conclusion, Ryanair demonstrates a more accurate implementation of cost leadership strategies, while Pegasus achieves higher customer satisfaction by adopting a flexible, hybrid model. This contrast highlights the challenge of balancing cost efficiency with customer expectations in the low-cost airline industry.

These findings contribute to the literature by offering a novel AI-driven methodological approach and providing managerial insights for airline executives striving to balance cost efficiency and customer satisfaction.

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