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RECOVERY OF THE AIRLINE PROVIDERS AFTER PANDEMICS: INCORPORATING QUALITY MEASURES TO MEASURE TECHNICAL EFFICIENCY

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Abstract—This study measures how the COVID-19 shock altered airline efficiency worldwide. Quarterly data (2014-2024) for fleet, fuel, labor and maintenance inputs and traffic/output indicators are evaluated with DEA, including an extended network slack-based model that delivers both optimistic and pessimistic efficiency bounds. Results show a 14 % median drop in technical efficiency during 2020-2021, with only three carriers—Singapore Airlines, Swiss and Wizz Air - remaining fully efficient. By 2024, recovery is incomplete; half the airlines still operate below 95 % of their 2019 frontier level, and dual-frontier gaps reveal sizeable hidden slack. Additional analysis confirms that a strong "green" image and service reputation cushion the efficiency loss, explaining why brands like Emirates retain higher overall ratings despite similar operations. The findings stress a post-pandemic agenda that balances cost control with service quality and sustainability.

Keywords: airlines, efficiency, pandemics, low-cost, full-service.

1. INTRODUCTION

Airline efficiency is no longer defined solely by operating with an optimal input-to-output ratio; in current academic debate, it has stabilized as a complex, multi-layered phenomenon. Technical–operational and financial productivity—captured, for example, by the Malmquist index or DEA scores—remains the core of any assessment because it directly reflects a carrier's ability to transform scarce resources (fleet, fuel, labor) into the desired volume of safe flight operations. Distinct efficiency patterns emerge across Europe, Asia, Latin America, and North America. European studies highlight liberalization pressures that favor smaller, more agile airlines [1]. In Asia, a handful of state-backed "champions" dominate, whereas the Brazilian and Indian markets still offer scope for scale-efficiency gains [2]. In the United States, post-pandemic data reveal a narrowing performance gap between different business models [3].

2. LITERATURE REVIEW

Service quality and passenger satisfaction are equally critical. Empirical studies confirm that SERVQUAL dimensions—reliability, empathy, responsiveness, and so forth—correlate strongly with repeat purchase behavior and an airline's ability to command revenue premiums [4]. An analysis of 1341 online passenger reviews at Honolulu Airport [5] revealed a direct link between clean infrastructure/workspaces and overall satisfaction. South African carriers demonstrated that the quality of service-recovery processes—how well problems are fixed—directly boosts customer loyalty [6]. Messner showed that any "value-for-money" strategy must be tailored to the economic and hedonic traits of a given market [7]. Herjanto et al. confirmed that glowing reviews do not always imply flawless service; customers are often delighted by a well-managed recovery effort [8]. Using Royal Jordanian and Royal Brunei as cases, Jahmani quantified how service factors lift satisfaction and brand image. The assessment of quality has widened to ground handling as well, where persistent gaps remain between expectations and actual performance [9], [10], [3].

Environmental and innovation performance—covering green initiatives, investment in fuel-efficient technology, and the rollout of digital solutions (NDC, IoT)—has evolved from a mere reputational bonus to both a regulatory requirement and a competitive advantage. In today's market, data analytics plays an ever-larger role in optimizing services, personalizing the customer experience, and sharpening decision-making across service industries, aviation included. Turning vast data streams into actionable insight lets airlines react quickly to changing traveler needs and lift key performance indicators. Srinivas and Ramachandiran showed that unstructured online reviews can, through advanced machine-learning tools such as topic modelling and sentiment analysis, be converted into concrete service-improvement ideas [11]. Analyzed in this way, customer data gives managers a clear view of service weak spots while highlighting areas that can strengthen brand competitiveness. Technological progress is also reshaping distribution. Štilić et al. noted that the shift from traditional global distribution systems (GDS) to newer frameworks such as New Distribution Capability (NDC) and the Internet of Things (IoT) is profoundly altering how airline products reach the market [12]. This change forces airlines to deliver consistent quality across digital and physical channels and enables more precise targeting of offers and ancillary services.

Digitalization also opens new avenues for revenue generation. Yoon and Lee showed that a "pay-to-upgrade" option—letting passengers pay for a better seat during booking or check-in—raises revenue while leaving passenger satisfaction unchanged, thereby optimizing capacity without harming the travel experience [13].

Psychological factors matter as well. A study from Pakistan found that "assurance"—customers' trust in an airline's competence and reliability—exerts the strongest influence on satisfaction and loyalty [14]. This underscores the value of credible, professional staff behavior when building long-term customer relationships. Importantly, the link between service quality and satisfaction is not linear: it is moderated by each traveler's price sensitivity and quality preferences, signaling the need for market segmentation and tailored communication.

Sustainability adds another layer. Wu et al. showed that perceptions of "green" quality and an eco-friendly brand image lower customers' propensity to switch carriers [10]. Environmental initiatives, therefore, deliver more than reputational gains; they directly support customer retention [15]. Evaluating airline performance today demands a multidimensional analytical toolkit that accounts not only for operational inputs and outputs but also for organizational design, regional constraints, and competitive strategy. Against this backdrop, Data Envelopment Analysis (DEA) and its extensions have proved robust for pinpointing technical efficiency and benchmarking decision-making units (DMUs). Using a classic DEA model on 29 European flag carriers, Żółtaszek and Pisarek found that size does not automatically translate into efficiency; several large airlines performed below smaller rivals. Their work sparked a wider debate on the central roles of managerial quality, capacity utilization, and input mix in achieving balanced performance [1].

Extended DEA approaches deepen the analytical toolbox even further. Several authors have applied the network slack-based measure with dual frontiers, allowing simultaneous identification of optimistic and pessimistic efficiency bounds for 24 global airlines [16]. This multi-layer view captures variability within network processes and yields a more realistic diagnosis of performance reserves [17]. Temporal benchmarking was tackled by Malhotra et al., who examined 14 Asian carriers from 2015-2019 and found that only three remained consistently efficient, underscoring how external shocks, market liberalization, and technological change destabilize performance [18]. These "role-model" airlines offer concrete examples for lower performers to emulate in resource allocation and strategy [19].

At a finer scale, Gomes Júnior et al. studied Brazilian airlines with a non-radial DEA model, showing the value of defining "real" target units—performance levels that are demonstrably attainable and thus more useful for benchmarking and strategic planning [20]. Sakthidharan and Sivaraman (2018) used DEA to dissect cost inputs in Indian carriers, pinpointing maintenance as the main driver of technical inefficiency and highlighting the savings potential of streamlined processes and preventive servicing. Together, these cases illustrate the power and flexibility of DEA—from simple ratio models to advanced network and non-radial variants—for uncovering performance gaps, setting realistic targets, and motivating strategic change [2].

When combined with rich data and complementary techniques such as sentiment analysis or multidimensional quality-and-sustainability indices, DEA can greatly enhance decision-making in aviation. Multiple studies confirm that (1) satisfaction drives loyalty, which drives repeat purchases, and (2) brand image mediates the link between service quality and loyalty [21-23]. Crucially, even if two airlines deliver identical service levels, the one with higher perceived value and stronger image (e.g., Korean Air, Emirates) is judged more efficient. Such a broad framework is essential because modern competition in aviation marries cost pressure with demands for high service quality and rising public sensitivity to environmental, safety, and social issues [24]. Without simultaneous optimization of all four dimensions -operations, service, reputation, and sustainability, carriers risk operational success but customer loss, reputational damage, or an inability to absorb shocks. A holistic view of efficiency is therefore key to sustainable competitiveness in twenty-first-century aviation [23].

The present study aims to assess how the technical efficiency of selected airlines changed before and after the COVID-19 pandemic and to determine their actual post-pandemic efficiency status. H1: The COVID-19 pandemic significantly reduced the technical efficiency of the analyzed airlines, and most carriers have not fully returned to their pre-pandemic efficiency levels in the post-COVID period. H2: Post-pandemic inefficiency is driven mainly by scale effects (inappropriate size and network capacity) rather than by a decline in pure technical efficiency of operations. This contribution has three main scientific outcomes. First, offers a systematic DEA-based comparison of pre- and post-COVID technical efficiency for selected global airlines, capturing both the depth of the efficiency shock and the extent of recovery. Second, by decomposing efficiency into pure technical and scale components across different business models, it clarifies whether post-pandemic weaknesses arise mainly from internal processes or from inappropriate scale. Third, it links these findings to the literature on service quality, brand image, and sustainability, promoting a more holistic interpretation of DEA results for rebuilding resilient, sustainable airline efficiency.

3. MATERIALS AND METHODS

3.1. Measurement of efficiency

Based on the literature review, the Data Envelopment Analysis method is the most appropriate method to measure technical efficiency not only in the field of airline services. Theoretical foundations have been developed by several authors [25], [26], [27], [28]. The main purpose of this method is to measure how efficiently inputs turn into outputs in selected Decision Making Units (DMU), in our case, the airlines. The most commonly used models are CCR (1) (constant returns to scale assumption) and the BCC (2) models (variable returns to scale assumption).

$$\begin{gathered}\min_{\theta_B,\lambda} \theta_B \\ \text{s.t. } \theta_B x_o - X\lambda \geq 0 \\ Y\lambda \geq y_o \\ \lambda \geq 0.\end{gathered} \tag{1}$$

$$\begin{gathered}\min_{\theta_B,\lambda} \theta_B \\ \text{s.t. } \theta_B x_o - X\lambda \geq 0 \\ Y\lambda \geq y_o \\ e\lambda = 1 \\ \lambda \geq 0.\end{gathered} \tag{2}$$

In this study, technical efficiency is evaluated using the input-oriented CCR and BCC Data Envelopment Analysis (DEA) models. The CCR model assumes constant returns to scale. Under this assumption, the model captures both pure technical efficiency (how well inputs are transformed into outputs) and scale efficiency (whether the airline operates at an appropriate size). By contrast, the BCC model allows for variable returns to scale and introduces a convexity constraint, meaning that each decision-making unit is only compared to feasible combinations of observed units of similar scale. Intuitively, CCR answers the question "How much could this airline proportionally reduce its inputs if it were operating on the global best-practice frontier?", while BCC answers "How efficient is this airline relative to peers of comparable size, abstracting from scale effects?" For a precise explanation of both models, refer to [25].

3.2. Data and research object

To meet the study objective, we have identified 3 input variables

- Fleet size – absolute number of aircraft
- Operating expenses – in million €
- Employees – absolute number of employees

and 2 output variables

- Skytrax Score
- Load factor – ratio of used vs. available capacity.

All these variables are, based on the literature review, commonly used indicators to measure airline efficiency. We have also incorporated the Skytrax Score retrieved from the Skytrax website, which reflects the value of perceived quality. The remaining indicators were obtained from the internal documents of the individual airlines.
Based on the availability of the data and to meet geographical heterogeneity, we have identified 13 airlines – 10 full-service and 3 low-cost airline providers (easyJet, Wizz Air, and Ryanair.

Table 1 Descriptive statistics of inputs

DMU	Fleet Size		Operating Expenses		Employees	
	Mean	SD	Mean	SD	Mean	SD
ANA All Nippon Airways	247	42	11067	1922	38000	4583
Asiana Airlines	84	2	6133	306	9967	451
Cathay Pacific Airways	160	18	9733	802	22333	3215
Emirates	249	28	25967	3769	83667	9018
Japan Airlines	164	8	9433	1002	35667	3512
Lufthansa	327	29	38500	4814	127333	8622
Qatar Airways	250	35	13533	7500	47633	5164
Ryanair	447	140	8767	3253	16833	7251
Singapore Airlines	125	21	9967	2371	26333	2517
Swiss International Air Lines	94	3	5300	700	9333	764
Thai Airways	346	88	12067	2250	24333	6506
Wizz Air	123	71	2567	1350	4300	2563
easyJet	293	59	7000	1510	10500	2291

Table 2 Descriptive statistics of outputs

DMU	Skytrax Score		Load Factor	
	Mean	SD	Mean	SD
ANA All Nippon Airways	98.33	0.58	76.20	2.30
Asiana Airlines	91.00	2.00	81.37	1.14

Cathay Pacific Airways	97.67	2.08	83.70	0.40
Emirates	97.00	1.00	80.37	0.81
Japan Airlines	93.67	1.53	73.77	3.27
Lufthansa	92.67	2.08	80.43	1.22
Qatar Airways	99.67	0.58	83.67	1.15
Ryanair	73.33	3.06	90.73	6.71
Singapore Airlines	98.67	0.58	84.33	3.86
Swiss International Air Lines	91.00	1.00	83.50	1.25
Thai Airways	95.67	1.53	81.00	1.87
Wizz Air	71.33	3.06	89.87	4.49
easyJet	76.00	2.00	90.97	0.47

Data were collected for the years 2014, 2019, and 2024 to observe a trend before COVID-19 and after COVID-19. Using a DEA window approach, we then obtained 39 individual DMUs (13 airlines and 3 years).

Across the 13 carriers in the dataset, three strategic archetypes emerge: (i) premium network airlines such as ANA, Cathay, Emirates, Qatar, Singapore and Swiss, which combine mid-to-large fleets, high operating expenditure and industry-leading Skytrax scores (97–99) with solid load factors (80–84 %), reflecting a quality-and-scale orientation; (ii) legacy megacarriers Lufthansa, Japan Airlines and Thai, whose very large fleets and workforces translate into the highest cost bases but only moderate service ratings (83–94) and below-peer utilization (70–80 %), hinting at scale diseconomies; and (iii) ultra/low-cost operators Ryanair, Wizz Air and easyJet, characterized by large homogeneous fleets, minimal service scores (74–82), rock-bottom unit costs and near-maximum load factors (89–95 %), epitomizing density-driven efficiency. Collectively, these statistics imply that any efficiency assessment must disentangle scale effects (via, e.g., BCC vs. CCR DEA models) to avoid penalizing mega-carriers for size, and should focus on cost and asset-utilization drivers, rather than service quality or load factor, to explain residual performance differentials.

4. RESULTS

In this section, we will provide results of the analysis with a focus on measuring efficiency and related analyses. In Figure 1, we can find a spider graph of the CCR model results, and in Figure 2, the BCC model results.

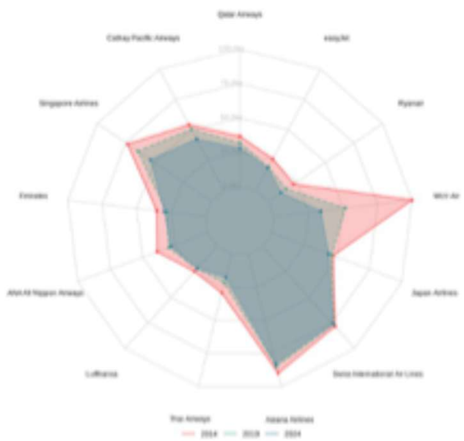

Figure 1 CCR efficiency results comparison

Across the thirteen carriers, CCR efficiency steadily erodes from 2014 to 2024, indicating that—at existing scale—most airlines are deploying fleet, labor, and spending less productively over time. The sharpest drops appear at Wizz Air (1.00 to 0.34) and Qatar Airways (0.37 to 0.28), revealing growing scale inefficiency even while their internal processes remain strong. Lufthansa, Thai Airways and Emirates already start from low CCR scores and slip further, showing that both their size and operations are out of alignment with best-practice benchmarks. By 2024 the widest CCR benchmark gaps (more than 0.70 below the frontier) belong to Ryanair, Lufthansa and Thai, signaling the greatest potential gains from resizing fleets or networks rather than merely cutting costs.

Figure 2 BBC efficiency results comparison

BCC efficiency, which isolates pure operational performance, declines far more modestly and stays at 1.00 for Singapore Airlines, Swiss, Wizz Air, Asiana (through 2019), and Qatar (through 2019), confirming that these carriers run near best practice once scale effects are removed. Cathay Pacific and Qatar remain highly process-efficient (approx. 0.78–0.98) despite their weak CCR efficiency, underscoring that their main issue is an oversized fleet. Emirates, ANA, Lufthansa, and Thai show persistent BCC scores below 0.65, revealing genuine process shortfalls in addition to scale problems. Ryanair's BCC gets to 1.00 in 2019 and retreats to 0.70 in 2024, suggesting a temporary procedural improvement that was not sustained. Overall, the BCC frontier highlights which airlines must refine day-to-day operations (low BCC) versus those needing to rebalance scale (high BCC but low CCR).

In Figure 3, we can see the results of the 2019 and 2024 comparisons of DEA CCR efficiencies, and in Figure 4, the case of BCC efficiency.

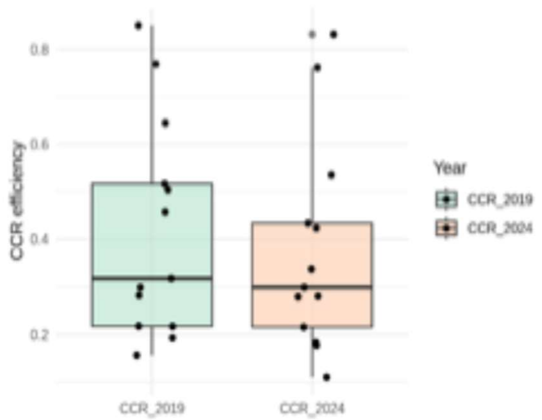

Figure 3 Box plots of the DEA CCR model results in 2019 and 2025

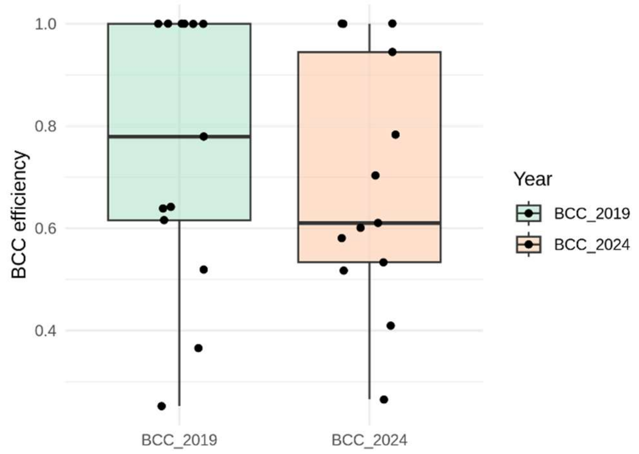

Figure 4 Box plots of the DEA BCC model results in 2019 and 2025

We have performed a paired t-test to check the null hypothesis that there is no significant efficiency change on average. In the case of the CCR model, there was a statistically significant decline in efficiency in the year 2024 ($p = 0.013$), but not in the case of the BCC model ($p = 0.14$).

Figure 5 and 6 consists of box plots, describing the differences of the efficiency between 2024 and 2019 (delta eff.)

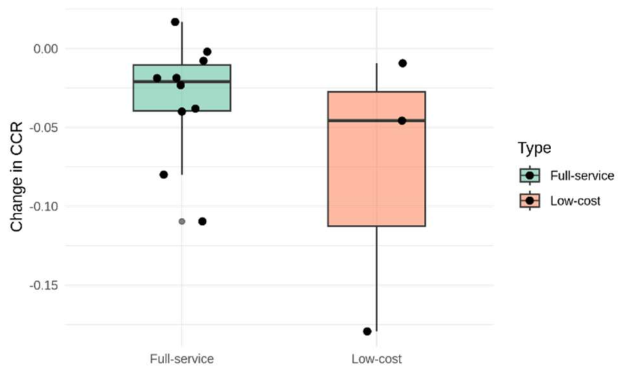

Figure 5 Box plots of the deltas DEA CCR efficiencies by the type of provider

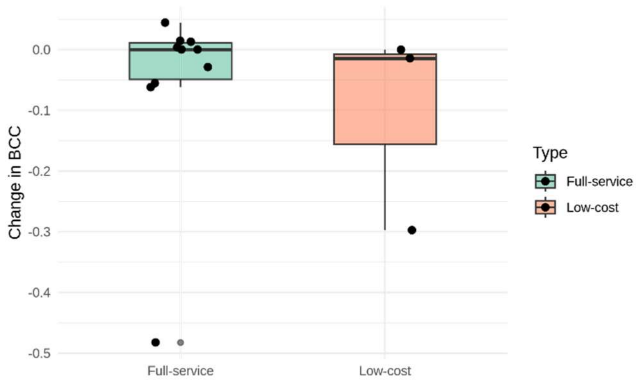

Figure 6 Box plots of the deltas DEA BCC efficiencies by the type of provider

We have performed the Welch t-test to check whether there is no significant change in efficiency (null). The results confirmed that we failed to reject the null hypothesis since the p-value for the CCR is 0.47 and for BCC is 0.68. The pandemic and cost-pressure period appear to have reduced technical efficiency across the board, regardless of whether the airline is low-cost or full-service

In Figure 7 and Figure 8, there are box plots of efficiency differences between 2024 and 2019 grouped by the airline provider size.

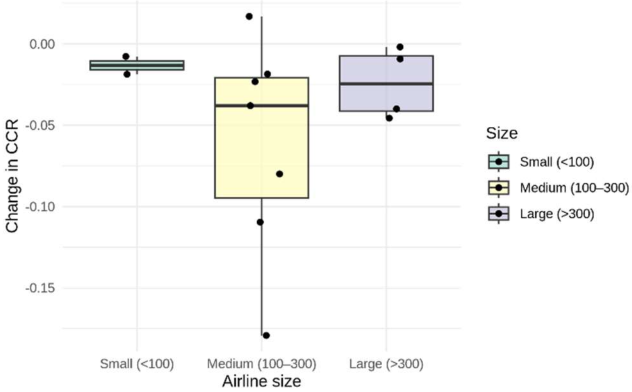

Figure 7 Box plots of the deltas DEA CCR efficiencies by the provider size

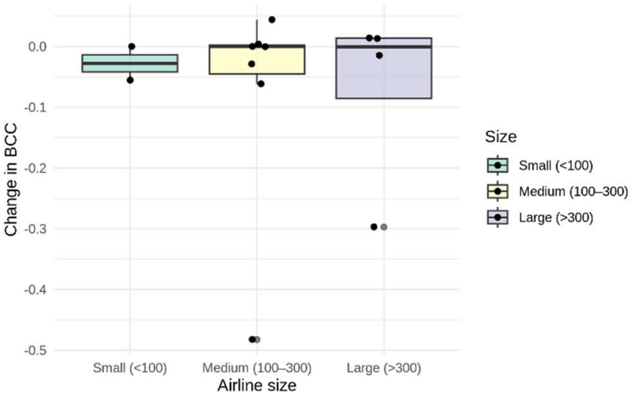

Figure 8 Box plots of the deltas DEA BCC efficiencies by the provider size

The one-way ANOVA test was performed to check whether there might be significant differences among efficiency results in both CCR and BCC DEA models. Since the F-statistics for the CCR model was 1.0 ($p = 0.40$) and for the BCC model $F=0.07$ ($p = 0.94$), we failed to reject the null hypothesis of equal means in both models.

5. DISCUSSION

Airlines face two kinds of efficiency problems: how well they run their day-to-day operations and whether they are the right size. Our numbers show that most premium carriers (Singapore, Qatar, Cathay, Swiss) still maintain their flights properly, but they have grown too large, so each additional plane now creates less value. Their priority is to trim capacity—retire older jets, cut marginal routes, or share lift through alliances—before chasing more minor cost savings.

The traditional groups: Lufthansa, Thai, ANA, Emirates, struggle on both fronts. Complex fleets, several hubs, and heavy staffing make their processes slow and expensive, and their networks are larger than demand justifies. They need deeper fixes: simpler fleets, fewer bases, and tighter labor rules, not just another round of cost-cutting.

Ultra-low-cost carriers show the opposite risk. Ryanair and Wizz Air still fill seats better than anyone, but our analysis warns that nonstop growth is starting to lower overall efficiency. Airport congestion, new green taxes, and crew shortages mean that adding planes no longer guarantees lower unit costs.

For policymakers, widening gaps between "how big" and "how well" airlines operate suggest that slot rules, carbon fees, and recovery grants can push companies beyond their efficient scale. Well-meant regulation should avoid encouraging expansion for expansion's sake.

Finally, the DEA method, with concern for both constant-returns (CCR) and variable-returns (BCC) DEA scores, proved useful to separate scale problems from process problems. Future studies should add carbon emissions and service quality (on-time, customer ratings) to paint a fuller picture, and perhaps use stochastic models to filter out one-off shocks like pandemics or fuel spikes. From a managerial perspective, the combined DEA, t-test and ANOVA results suggest that airlines should (i) systematically monitor efficiency changes across periods rather than relying on single-year snapshots, and (ii) design recovery strategies that are tailored to their business model and scale, as statistically significant differences between groups indicate that "one-size-fits-all" solutions are unlikely to be effective. In practice, this means using DEA and simple statistical tests as a regular benchmarking toolkit to identify whether observed performance gaps are random, pandemic-related, or rooted in deeper structural issues.

This study has several limitations that affect how its results should be interpreted. First, the DEA framework captures only a simplified version of airline production based on a restricted set of quantitative inputs and outputs, without fully incorporating strategic choices, labor relations, alliance effects, or detailed network design. Technical efficiency scores are therefore sensitive to how the model is specified and to data quality. Because DEA is deterministic and does not use a stochastic frontier, bootstrapping or confidence intervals are not employed. Consequently, we cannot clearly distinguish between true inefficiency and random shocks or measurement error, especially during the highly unusual pandemic years. Second, the sample covers only selected medium and large carriers, focusing mainly on operational efficiency, while service quality, customer satisfaction, brand image, and environmental performance are discussed more conceptually than explicitly modeled. Airlines that intentionally trade some cost efficiency for higher service or greener operations may thus appear relatively inefficient in this setting. The absence of extensive robustness checks (alternative input–output sets, different model variants, or scenario analyses excluding extreme years) further limits generalizability. Future research should broaden the dataset, integrate quality and sustainability metrics directly into the efficiency model, and complement DEA with stochastic and robustness methods to obtain a more holistic and statistically resilient view of post-pandemic airline performance.

6. CONCLUSION

Across the 13 global carriers, a clear typology emerges that shapes both their resource structures and efficiency trajectories. Premium network airlines (e.g., Singapore Airlines, Qatar, Cathay, Emirates, ANA, Swiss) combine sizable fleets and high operating expenditures with industry-leading Skytrax scores, whereas megacarriers (Lufthansa, Japan Airlines, Thai) exhibit comparable scale but lower service quality and utilization, and ultra/low-cost operators (Ryanair, Wizz Air, easyJet) prioritize minimal unit cost and maximal load factors at the expense of service differentiation. Descriptive statistics confirm that premium and ULCC strategies can each yield high load factors, yet the underlying cost structures diverge markedly—premium airlines incur greater absolute expenditure while ULCCs compress costs through homogeneous fleets and dense seating configurations.

Data-envelopment analysis (DEA) reinforces these structural insights. Under the constant-returns-to-scale (CCR) model, efficiency scores fall for nearly all carriers from 2014 to 2024, signaling mounting scale inefficiency as fleets and networks expanded faster than productive capacity. The steepest CCR declines at Wizz Air and Qatar Airways suggest that rapid growth, even from an initially efficient base, can overshoot the optimal scale envelope. Conversely, legacy full-service operators (Lufthansa, Thai, Emirates) persist at low CCR levels, indicating entrenched scale diseconomies that have not been addressed over the decade. The magnitude of the CCR–BCC gap (up to 0.72 in 2024 for Qatar) quantifies the potential gains from right-sizing rather than purely improving internal processes.

Variable-returns (BCC) results isolate pure operational performance and reveal a more nuanced picture. Singapore Airlines, Swiss, and Wizz Air remain on or near the BCC frontier throughout, confirming world-class process efficiency once scale distortions are removed. Cathay Pacific and Qatar also retain high BCC scores (> 0.78), underscoring that their primary inefficiency is now macro-structural, not procedural. In contrast, Lufthansa, ANA, Thai, and Emirates register persistent BCC values below 0.65, evidencing substantive internal inefficiencies alongside scale misalignment. Ryanair's temporary BCC spike to unity in 2019, followed by retreat in 2024, suggests that operational improvements can be fragile without sustained managerial focus.

Taken together, the evidence indicates that future efficiency gains will require differentiated strategies. Carriers with high BCC but low CCR (Qatar, Cathay, Singapore, Swiss, Wizz Air) should prioritize capacity optimization through fleet rationalization, network pruning, or alliance restructuring to recover lost scale efficiency. Airlines exhibiting dual inefficiencies (Lufthansa, Thai, Emirates, ANA, easyJet) must pursue a dual agenda: lean-process initiatives (digital workflow, crew productivity, maintenance analytics) coupled with judicious resizing to approach the variable-returns frontier. Finally, ULCCs should recognize that sustained hyper-growth risks erode their historical efficiency advantage, necessitating disciplined expansion tempered by continuous process vigilance.

Methodologically, the combined descriptive clustering and two-stage DEA approach proves effective for disentangling scale vs. pure technical effects in a heterogeneous industry. Policy-wise, regulators and investors should interpret rising inefficiency not merely as managerial underperformance but as a signal that market structures—airport slot constraints, environmental regulation, and post-pandemic demand shifts - may be pushing carriers beyond their efficient production sets.

Future work could integrate environmental inputs (emissions) and quality-adjusted outputs to yield a more holistic frontier, particularly as sustainability mandates intensify across aviation. Future work could extend this study by incorporating richer quality and sustainability indicators directly into the efficiency model and by combining DEA with panel regressions or stochastic frontiers. This would allow researchers to link statistically significant group differences not only to cost and capacity factors, but also to service quality, environmental performance, and brand-related variables, providing a more complete picture of post-pandemic competitiveness in the airline industry.

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