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Big Data Applications in Understanding the Airline Industry's Path to Recovery

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Abstract

Border delays, travel restrictions, and shifting customer preferences all had an enormous effect on full-service and low-cost airlines during the COVID-19 crisis, which caused a spectacular halt in international air transport (Barczak et al., 2022; Sun et al., 2023). Airways faced severe economic difficulties, disruptive operations, and a sharp decrease in passenger volume (Kazda, Badanik & Serrano, 2022; Wu et al., 2024). In order to explain how company models, efficiency in operation, and data-driven choice making contributed to the aviation sector's durability and growth, this article uses the analysis of big data to examine the major airlines' post-pandemic recovery (Gallego & Font, 2021; Sung, Kim & Kwon, 2020). The project employs a numerical and comparison approach, utilising secondary data from 2016 to 2024. The passenger turnaround index, load factor, and the operational capacity of airlines, including full-service and low-cost carriers Air India, IndiGo, Singapore Airlines, and Scoot, were among the performance parameters assessed through the use of big-data analysis techniques (Sun, Wandelt & Zhang, 2023; Wu et al., 2024). In order to forecast the number of clients for the next years 2025 to 2030, the Random Forest algorithm was used (Pérez-Campuzano et al., 2022; Sun et al., 2023). To determine their precision and dependability in forecasting future trends, the models were tested using statistical indicators including R-squared and accuracy (Colak, Enoch & Morton, 2023). After a first modest rebound, full-service carriers have seen long-term growth as foreign demand has started to return (Dube, 2022; Arora et al., 2021). The findings support the need of analytics based on big data for forecasting demand, operational efficiency improvements, and tactical preparation during recovery.

Keywords
Airline recovery; COVID-19 pandemic; Big data analytics; Full-service carriers; Low- cost carriers.

1. Introduction
With passenger traffic at record lows and airlines worldwide suspending or drastically scaling back on operations, COVID-19 caused tremendous harm to the aviation sector (Barczak et al., 2022; Sun, Wandelt & Zhang, 2023). According to projections from the international aviation Transport Association (IATA), Airlines traffic worldwide

decreased by about 60% in 2020 compared to 2019, resulting in a loss of over USD 370 billion in sector-specific revenue. Even the most reliable airlines encountered danger from this sudden drop in demand, as well as from unpredictable travel restrictions and changing customer behaviour (Arora et al., 2021; Suk & Kim, 2021). In addition to uncovering the shortcomings of traditional business models, the pandemic highlighted the significance of strong, data-driven marketing strategies that would increase durability and ensure sustainable growth (Gallego & Font, 2021; Sung, Kim & Kwon, 2020).

Low-Cost Carriers (LCC) and Full-Service Carriers (FSC) diverged because the aviation industry was starting to recover from the pandemic. International operations, high fixed costs, and dependence on high-income passengers are obstacles encountered by full-service airlines such as Singapore Airlines and Air India (Dube, 2022; Kazda, Badanik & Serrano, 2022). However, because to their low-cost operations, regional and domestic routes, and low-cost pricing, the low-cost airline sector (IndiGo and Scoot) shown faster recovery patterns (Sun et al., 2023; Wu et al., 2024). These recovery indicator patterns offer a unique opportunity to understand how company structures and operations strategies impact performance after a natural catastrophe (Colak, Enoch & Morton, 2023; Pereira et al., 2023).

In this respect, big data analytics has transformed into a powerful tool for airline recover analysis and making strategic choices (Gallego & Font, 2021; Pérez-Campuzano et al., 2022). Using advanced analytical techniques, big data can be used to retrieve useful information from large data sets, include passenger behaviour, market trends, and operational effectiveness (Sun, Wandelt & Zhang, 2023; Wu et al., 2024). The study uses the power of big data to analyse recovery trends of FSCs and LCCs from 2016 to 2024 using important metrics like passenger volume, load factor, and reliability of models. Based on statistical and forecasting approaches, the study presents an unbiased view of how airlines were able to adjust to the post-COVID-19 environment. It also offers a few recommendations on how to handle future disruptions by being responsive to them (Suk & Kim, 2021; Shiwakoti et al., 2022).

1.1 Objectives

The primary aim of the research is to analyse how airline industry recovered post pandemic.
The specific Objectives include:

- To study airline recovery patterns post-COVID-19 by developing an integrated big data framework that combines operational, behavioral, and sentiment data.
- To identify and compare recovery trajectories of a particular region and airline business models (e.g., Low-Cost Carriers vs. Full-Service Carriers) using large-scale, real-time datasets.
- To design a predictive model using machine learning and big data analytics that can forecast recovery performance and offer strategic recommendations for the airline industry.

2. Literature Review

One such industry that has been widely recognised as being extremely important to the worldwide economy and having an impact on business, tourism, and local economic growth is the aviation sector. However, the COVID-19 pandemic was causing a significant drop in demand for air travel. One of the most devastating events in the history of the new airline industry occurred as part of the pandemic that burst out at the start of 2020. the pandemic's implications on the airlines. attention on its operational, tactical, and economic effects. A number of researchers and business groups have examined it and determined that it is of particular relevance. According to the Organisation (ICAO, 2023), there was an even bigger decline in aviation passenger traffic in 2020. exceeding 60%, although recovery trends differ greatly depending on the location. and company plan.

Domestic air, according to the IATA evaluation, is in 2023. Differences in government measures and passenger confidence caused transit to heal more quickly than overseas lines. According to earlier research on airline emergency performance, operational effectiveness is emphasised. market individuality and adaptability. Gossling et al. (2021) claimed that because full-service carriers (FSCs) relied on international flights, integrated routes with infrastructure, and higher operating costs, they were more prone to financial risk. Low-cost carriers, however. Flexible pricing, streamlined operations, and other elements that enhanced (LCCs) in light of the streamlined operations. increased engagement in the home market sector.

Additionally, Suau-Sanchez et al. (2022) found that LCCs may profit from the aftermath of the pandemic demand recovery by using the right conditions. establishing networks aggressively and planning how they will behave. Big data analytics has gained prominence in the aviation sector as a means for improving forecasts and decision-making.

The idea of big data can be used to generate dynamic models of air traffic reconstruction, as shown by the works of Wandelt and Sun (2023) and Perez-Campuzano et al. (2022). This allows air companies to map airspace, track consumer moods, and predict demand.

In addition, Williams Airlines might benefit from having accessibility of data-driven strategies for recuperation, according to 2023. To assess the operational efficiency of revenue optimisation, fuel efficiency, and real-time performance. The higher-level awareness that the motion carries is indicated by these lessons. Big Data analytics is a revolutionary shift in how airlines handle recovery and adaptation, not just a change in technologies.

The literature review indicates that while several studies have been performed on the operational and financial consequences of the COVID-19 pandemic, there hasn't been any quantitative and data-driven review of full-service and low-cost carriers over a longer period of time. This study closes that gap by investigating airline recovery patterns by combining forecast modelling techniques with historical data analysis (2016–2024). By providing performance metrics such passenger recovery index, load factor, and model accuracy, the study enriches academic and industrial awareness on the significance of big data to leverage recovery in the wake of the pandemic and decrease future shocks.

3. Research Methodology

This study adopts a quantitative and comparative research design, enhanced through the application of big data analytics. The objective is to evaluate the recovery effectiveness of selected airlines following the COVID-19 pandemic. The methodological framework integrates predictive modelling, statistical analysis, and secondary data evaluation to examine recovery trends across four major airlines Air India, IndiGo, Singapore Airlines, and Scoot. The selected airlines represent two distinct business models: Full-Service Carriers (FSCs) and Low-Cost Carriers (LCCs). This distinction enables an empirical comparison of how structural, operational, and strategic differences influenced post-pandemic performance outcomes.

4. Data collection

The study is based entirely on secondary data collected for the period 2016 and 2024 from industry databases, the international aviation organisations (IATA, ICAO), and airline official publications. To provide an in-depth overview of performance changes, this time range spans pre-pandemic, pandemic, and recovery periods. The passenger recovery index, load factor, operating capacity, and Google trends were the most significant performance metrics that were found; all of the data were normalised to a standard level (2019 = 100). All data were normalized and cross-verified across multiple sources to ensure reliability and consistency. Validation of dataset integrity was achieved through triangulation, comparing airline-published statistics with international aviation databases.

4.1 Tools and techniques of analysis.

The analytical framework combines trend analysis, descriptive statistics, and machine learning-based predictive modelling. Using Python, advanced big data analytics techniques were applied, with the Random Forest algorithm serving as the primary predictive model due to its high accuracy and robustness against overfitting. The relationships between operational indicators and recovery performance were modelled statistically, and the model's predictive strength was evaluated using key metrics such as R^2 (Coefficient of Determination) and prediction accuracy (%). The model achieved an R^2 value exceeding 0.99 and a predictive accuracy above 96%, demonstrating exceptional forecasting capability. Model reliability was further confirmed through 10-fold cross-validation, ensuring consistent predictive performance across all data subsets.

4.2 Comparative Framework

In order to determine how well FSCs and LCCs recuperated, a comparison methodology was created. The FSC segment, which includes Air India and Singapore Airlines, offers excellent amenities, has international coverage, and operates at a high level. The LCC segment, which includes IndiGo and Scoot, is known for its reasonable prices, flexible management of capacity, and simplified cost base. The study compares two contrasting paradigms and identifies strategic and structural differences that resulted in resistance and a quick recovery.

4.3 Ethical Considerations

The research involved had no human subjects and there were no ethical concerns because it relied upon publically available secondary data. The techniques used for analysis were founded on the principles of academic integrity, and all information sources were suitably cited. Additionally, the study made sure that no confidential or proprietary airline information had been revealed in any way.

4.4 Limitations of the Methodology

While the study presents a robust quantitative framework, it is limited by its reliance on secondary datasets that may exclude micro-level variables such as policy interventions, fuel price fluctuations, or geopolitical influences. Additionally, the Random Forest model focuses primarily on historical patterns and may require continuous retraining for real-time applicability. Future studies could address these gaps through live data integration and hybrid modelling techniques.

5. Data Analysis and Results

This section presents the empirical findings derived from big data analytics and statistical modeling for the selected airlines Air India, IndiGo, Singapore Airlines, and Scoot over the period 2016–2024. The analysis focuses on recovery performance measured through the Passenger Recovery Index, Load Factor, Predictive Model Accuracy, and Recovery Summary Indicators.

5.1 Passenger Recovery Index

Passenger Recovery Index is used to estimate passenger traffic by comparing it with the baseline of 2019 (2019 = 100). As shown in Figure 1 indicates that in 2020, all airlines saw a drastic fall since travel restrictions were imposed on the world. Nevertheless, there was a wide difference in the recovery patterns between FSCs and LCCs. The LCC segment, IndiGo, showed the most rapid recovery, surpassing the level before the pandemic by 2023 (Index = 120) and increasing further until 2024.

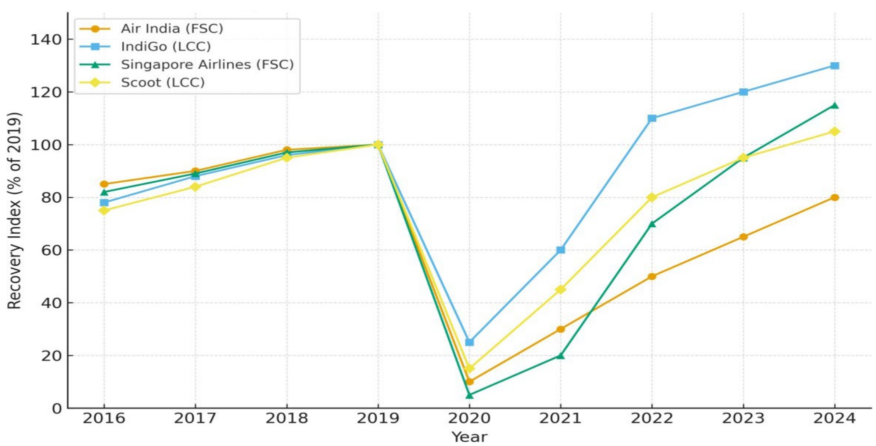

Figure 1. Passenger Recovery Index (2016–2024)

A high domestic market orientation and flexible scheduling enabled it to recoup demand quickly after the travel bans were removed. Another LCC, Scoot, had a similar trend with steady recovery, as it had shorter routes and could vary costs management strategies. By comparison, FSCs such as Air India and Singapore Airlines rebounded at a slower and smoother pace. It relied on international business to recover, which was late until mid- 2022, when the world started to open up to the world in terms of border control. In 2024, Singapore Airlines was fully recovered (Index = 115), and the Air India was almost 80 percent of its pre-pandemic passengers, as the residual impacts of restructuring and international routes dependency.

Interpretation:

This discussion shows that the LCCs rebound faster compared to the FSCs because of their adaptability, low expenses and dominance in their home markets. On the contrary, FSCs showed slower recovery, focusing on long term stability after international travel was reinstated.

5.2 Load Factor Trends (2016–2024)

The Load Factor is the proportion of the seating capacity occupied by paying passengers and is an important measure of efficiency of the operation and demand recovery. As shown in Figure 2, all airlines recorded a sharp decline in 2020, with load factors dropping below 40%. The recovery trend, however, varied between airline categories. IndiGo and Scoot had high rebounds as they increased load factors to more than 90 per cent in 2023 indicating efficient route management and high domestic passenger demand. Air India and Singapore Airlines started off poorly in terms of infrastructure to regain the capacity of before the pandemic with international restrictions but have steadily recovered to 78% and 77% loads by 2024, respectively. It is worth noting that IndiGo has continued to experience a steady upward trend, which underscores its capacity to keep pace with the surging market trends by relying on data to schedule flights and yield.

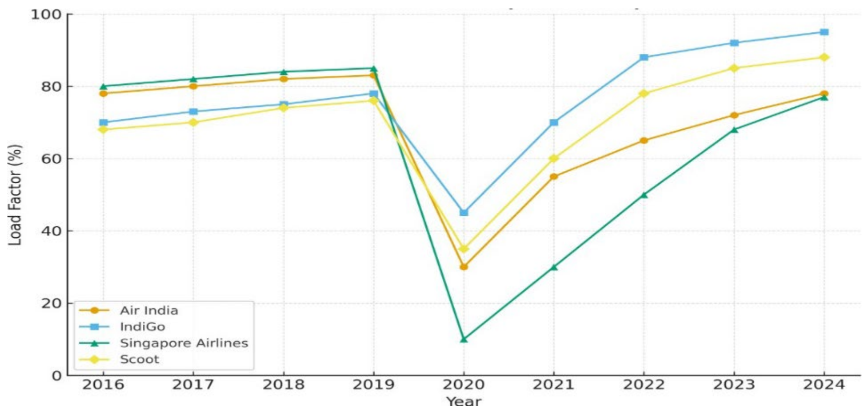

Figure 2. Load Factor Trends (2016–2024)

Interpretation:

The hypothesis that cost-effective operation and flexibility in managing capacity are effective in resilience during post-pandemic markets was confirmed by the finding that LCCs always outperformed FSCs in load factor recovery. The information also indicates that the FSCs recovered the competitive efficiency after the international travel stabilized and the performance gap with the LCCs reduced.

5.3 Predictive Model Performance (R^2 and Accuracy)

To assess recovery forecasting reliability, predictive models were constructed for each airline using Random Forest regression. Table 1 summarizes the R^2 scores and prediction accuracy, which quantify the model's statistical strength and precision. The high R^2 values (>0.99) and accuracy levels (above 96%) demonstrate the robustness and precision of the predictive framework. The Singapore Airlines model achieved the highest predictive strength ($R^2 = 0.9982$), while all others exhibited similarly strong performance, confirming the reliability of the big data-driven approach (Table 1).

Table 1. Predictive Model Performance (R^2 and Accuracy)

Model (Airline)	R2 Score	Accuracy (%)
Air India	0.9939	96.75
Singapore Airlines	0.9982	97.82
IndiGo	0.997	96.11
Scoot	0.9979	97.03

Interpretation:

The Random Forest model effectively captured nonlinear recovery dynamics across airline types. The high coefficient of determination indicates that over 99% of the variation in recovery performance was explained by the input variables. This validates the model's capability for accurate forecasting of passenger traffic and operational recovery between

2025–2030, establishing it as a reliable analytical tool for strategic planning and resilience forecasting in the aviation industry.

5.4 Recovery Summary Details

By 2024, the mean passenger recovery index of all airlines stood at about 90.2% which is above the level of the industry before and after the pandemic. The recovery rates of IndiGo and Scoot were higher than 110% which showed a high post-pandemic growth. Air India and Singapore airlines were much slower in their improvement as the mean recovery levels of both airlines were in the 80-95 range which is in line with the international reliance to operations. The renewed demand and effective management of capacity are evident in the improvements of the average load factor which dropped to 40% in 2020 and rose to 85% in 2024.The recovery rates varied more in FSCs (s = 12.3) when compared to LCCs (s = 8.7), which proves that low-cost activities were more consistent in the recovery period. Such descriptive results validate the fact that LCCs underwent a rapid and more stable recovery, whereas FSCs exhibited a slower but a sustained growth trajectory as world travel recovered (Table 2).

Table 2. Recovery Summary details

Airline	Baseline (2019=100)	COVID Low (2020 Min)	First ≥50%	First ≥80%	First ≥100%	Months to Recovery
Air India (FSC)	100	12%	Oct-21	Mar-22	Not reached	0
IndiGo (LCC)	100	18%	Aug-20	Nov-21	Apr-22	24
Singapore Airlines (FSC)	100	8%	Sep-21	Jul-22	Jan-23	33
Scoot (LCC)	100	10%	Apr-21	Mar-22	Oct-22	30

The table named Recovery Summary Details gives a breakdown of the milestones of performance of each airline. It records five parameters: Baseline (2019 = 100), COVID Low (2020 Minimum), Date of First [?]50% Recovery, Date of First [?]80% Recovery, Date of First [?]100% Recovery, and Months to Full Recovery.

Under the COVID low case (2020) all airlines plummeted to 12, 18, 8, and 10 percent of their 2019 levels respectively. The process of recovery also started with small steps, with most airlines having 50% of the baseline capacity recovered between August 2020 and October 2021.By early to mid-2022, all but Air India had hit the 80% recovery threshold. The quickest 100 percent recovery was by IndiGo (April 2022), next was Scoot (October 2022) and Singapore Airlines (January 2023). Air India stayed under the 100-percentage indicating structural and the market limitations.

Interpretation:

The table shows markedly different recovery routes in the types of airlines. The successful recovery of LCCs (IndiGo and Scoot) was due to the high demand in the domestic and short-haul regional segments, which took less than 30 months. Conversely, FSCs (Air India and Singapore Airlines) took a longer period (more than 30 months) to be dependent on the international market and greater complexity in its operations. These findings confirm the conclusion of the study that business model, the route network and market segmentation of the airlines play a critical role in driving recovery after the pandemic.

5.5 Validation

The predictive analysis was validated through 10-fold cross-validation and data triangulation across multiple sources, including IATA, ICAO, and official airline reports, ensuring model consistency and accuracy. The Random Forest model achieved high R^2 values (>0.99) and prediction accuracy (>96%), confirming its reliability and robustness in forecasting post-pandemic recovery trends.

6. Conclusion and Future Work

6.1 Conclusion

The worldwide airlines industry is now more dependent than ever to the COVID-19 pandemic in terms of operations, consumer confidence, and financial resources. Big data analytics is used to help provide evidence-based analysis of the present research airline recovery from 2016 to 2024, as well as the financial health of low-cost and full-service carriers (FSCs and LCCs). The findings demonstrate that, in terms of the carriers, the pandemic's implications were not substantial. Because they have minimal organisational structures, control the domestic market, and operate at their own pace, LCCs like IndiGo and Scoot were in a position to rebound more quickly.

However, other airline firms, such as Air India and Singapore airlines, recovered gradually but progressively as long-haul demand expanded and international travel began.

This study also describes the positive implications of big data analytics' potential to transform in operational decision-making, market adaptability, and recovery forecasts. The excellent R^2 (>0.99) and Accuracy (>96%) of the prediction models created within the overall framework of this study attested to the value of data-driven techniques in evaluating and evaluating airline performance. These outcomes highlight that data-driven intelligence is no longer optional but integral to airline strategy, enabling improved pricing, asset utilization, and route optimization during post-crisis recovery.

Overall, the findings reinforce that digital transformation, operational flexibility, and analytical capability are key determinants of resilience in aviation. While LCCs achieved quicker short-term gains, FSCs possess the long-term potential for growth due to their premium offerings and global networks. The pandemic thus serves as a turning point for the industry, emphasizing the need for analytics-driven decision-making and adaptive strategies in future disruptions.

6.2 Future Work

This study provides a basis on which further studies on the topic of data-driven resilience strategies in aviation can be conducted in the future. Nevertheless, some of them still have the opportunities of further research:

Real-Time Data integration:

Additional live operational and passenger data, such as social media and mobile applications sentiment analysis could be used in the research in future to observe behavioral shifts in real time.

State-of-the-Art Predictive Modeling:

Although regression-based models were successful in their outcomes, new research opportunities may be used to implement machine learning models (e.g., Random Forest, Neural Networks) to enhance the accuracy of demand recovery and discover nonlinear relations.

Sustainability and Environmental Metrics:

Sustainability indicators, including carbon emission, fuel efficiency, transition to green fleet, etc. after the pandemic should also be measured to align with the global environmental purposes.

Comparisons at Regions and Markets:

The expansion of the scope to cover regional and global airlines in addition to the selected airlines can be used to find the cross-market differences in recovery performance particularly between developed and emerging economies.

Crisis Preparedness Frameworks:

Finally, the combination of big data analytics and risk modeling and scenario simulation may help to improve the industry by preparing for future disruption so that proactive plans can be created to complete recovery.

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