Optimizing Air Travel: A Data-Driven Approach to Flight Delay Analysis and Prediction

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Project Objectives

01

Uncover Hidden Patterns

02

Develop Predictive Capability

03

Generate Actionable Insights

04

To help airlines minimize operational disruptions.

METHODOLOGY

I drop the columns with missing values because columns data depends on each other

Data Cleaning & Feature Engineering

Exploratory Data Analysis (EDA)

Performed data analysis on different columns

Balance the data , encode the categorial columns and applied different classification models

Classification (Delayed: Yes/No)

Regression (Delay Duration in Minutes)

Applied regression models on the data to know the expected average delay in minutes

By SHAPscore we can say that arr_flightsHeavily influences

Operational Adjustability Index(OAI) & SHAP

TOOLS USED : Python, pandas, matplotlib

MODEL USED : Linear and logistic regression , Random Forest Classifier and Regressor , XGBoost Classifier and Regressor

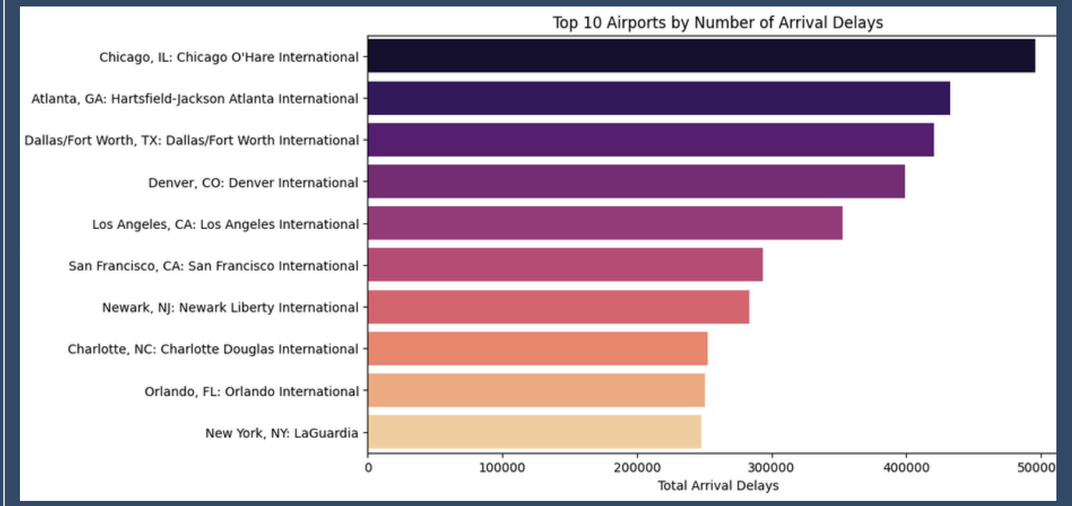
KEY FINDINGS

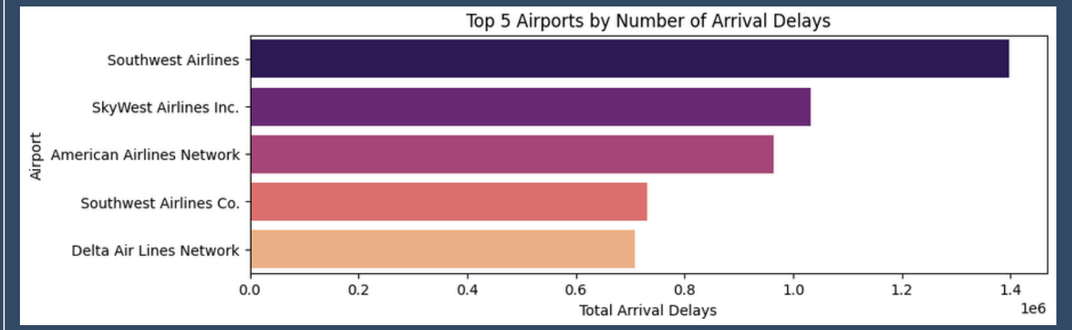
Patterns Identified:

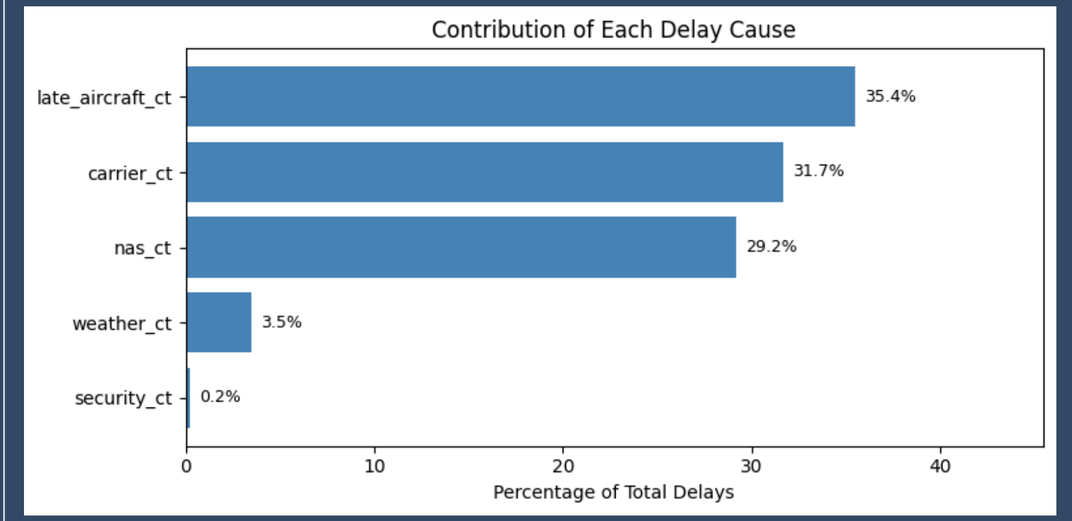
- Certain airports (e.g., Chicago, ATLANTA) show most delay
- SouthWest airline and Skywest airline show max delayed flights
- All airports are in major metros, suggesting delays stem from high traffic and complex networks.

Top Delay Drivers:

- Late Aircraft (35.4%) – Top delay cause; reflects tight turn arounds and poor schedule buffers.
- Carrier Delays (31.7%) – Airline-specific issues; opportunity for internal process improvement.
- NAS Delays (29.1%) – Air traffic/system inefficiencies; highlights need for ATC and airport upgrades.
- Weather + Security (3.75%) – Minimal impact overall, indicating smooth operations and favorable conditions.





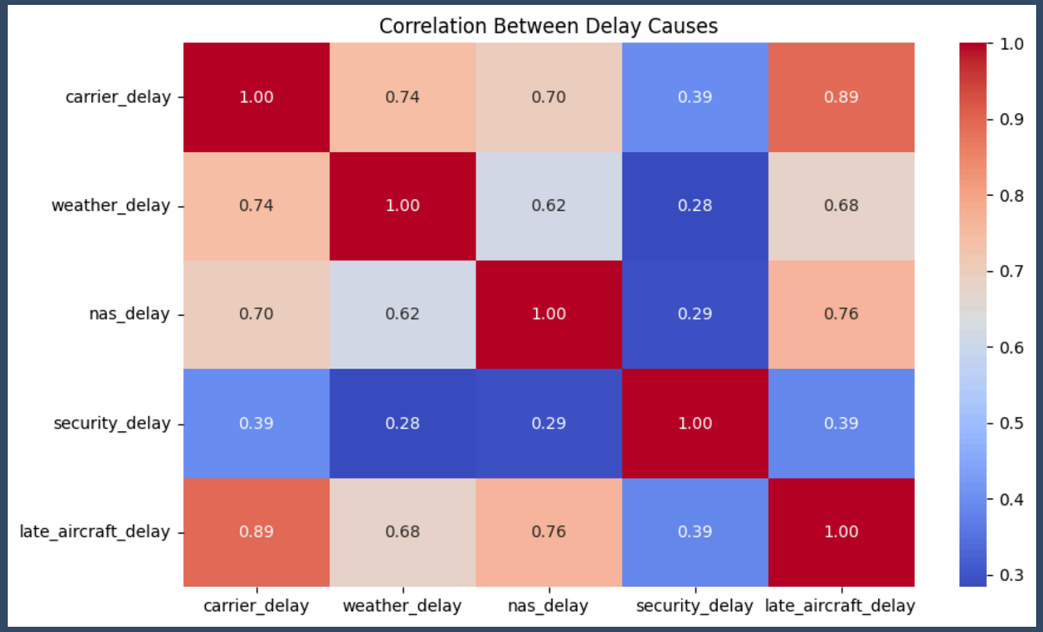


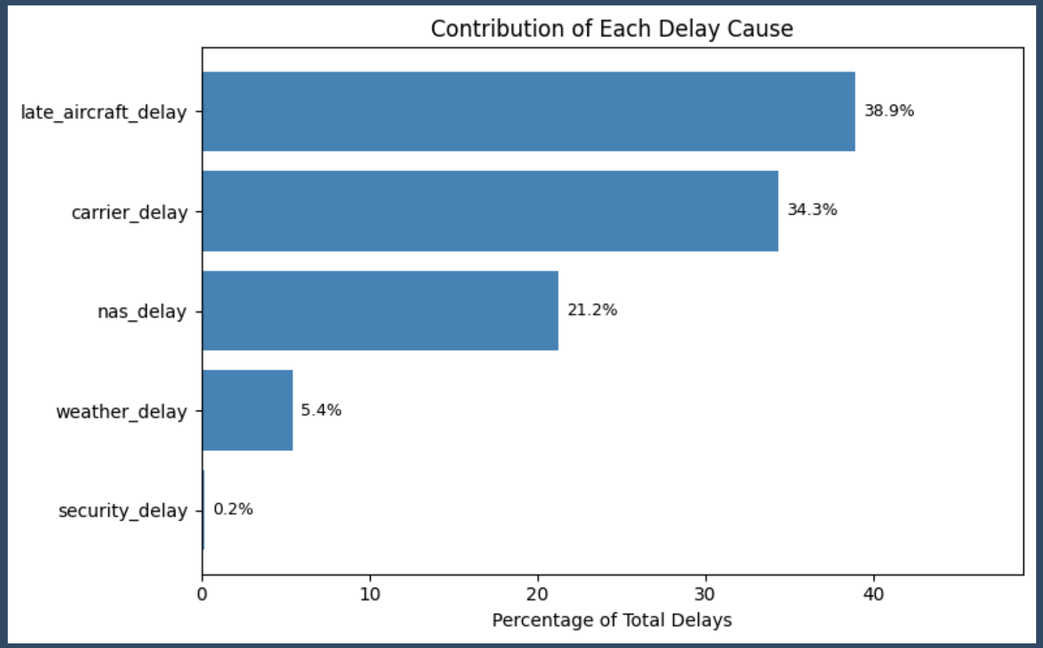
Correlation Between Delay:

- Late aircraft delays have the strongest correlations with other delay causes, especially carrier and NAS delays.
- Carrier delays are closely linked to both weather and system-related (NAS) issues.
- Security delays are rare and mostly independent of other causes.

Total Arrival Delay Distribution :

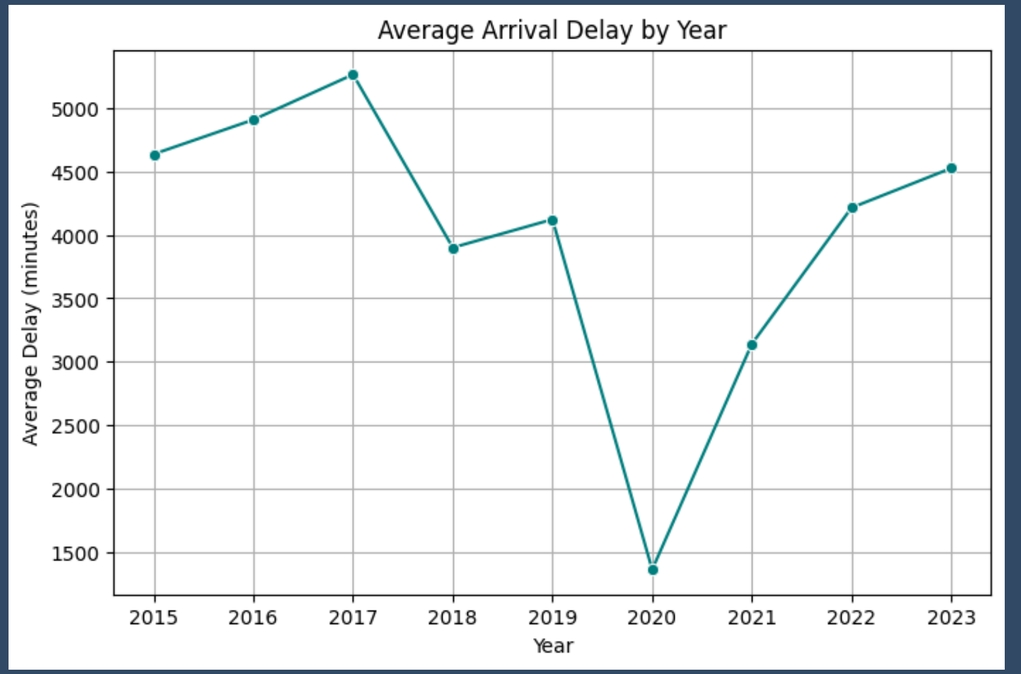
- Late Aircraft (38.89%) – Primary delay cause; due to previous flight arriving late, creating cascading delays.
- Carrier Delays (34.38%) – Airline-specific issues like crew, maintenance, or baggage handling inefficiencies.
- NAS Delays (21.24%) – Caused by traffic volume, congestion, and ATC-related inefficiencies.
- Weather + Security (5.49%) – Minor impact, likely due to favorable conditions and efficient safety protocols.





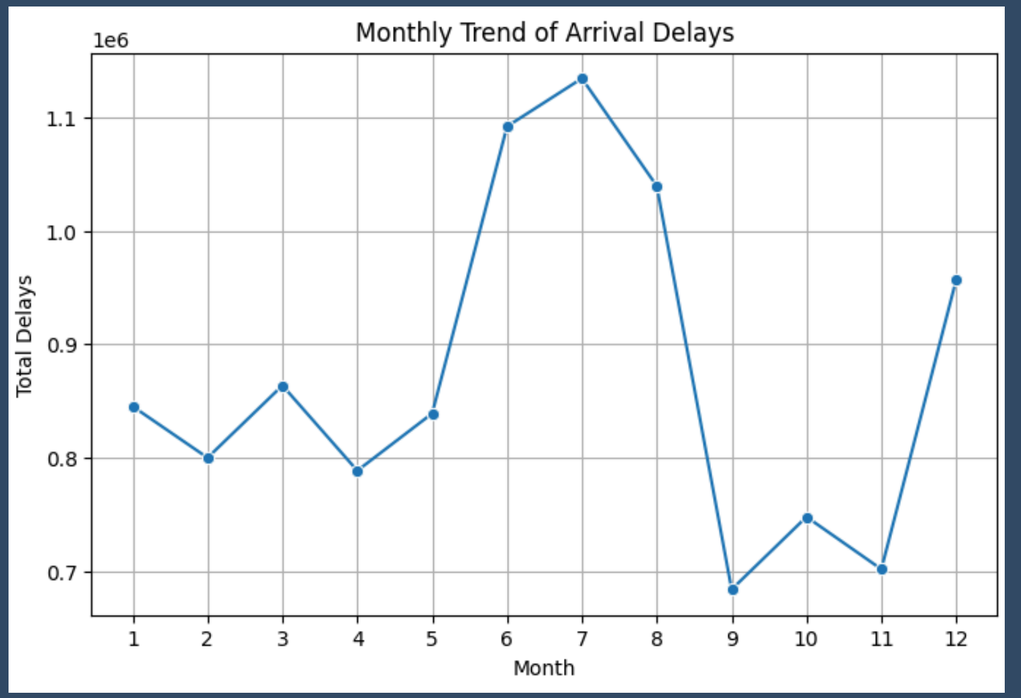
Average Arrival Delay by Year :

- Highest Delay: 2017 had the most delays — likely due to operational overloads.
- Lowest Delay: 2020 saw a sharp dropdue to the COVID-19 pandemic.
- Post-COVID Recovery: Delays climbed steadily from 2021 to 2023 (4400 mins) as flights resumed.



Total Delayed Flights by Month :

- Peak Delays: July, June, and August show the most delays — due to summer travel and monsoon impact.
- Lowest Delays: Sept, Nov, and Oct have the fewest delays likely due to lower demand and better weather.
- Moderate Months: January, March, and May show steady, moderate delays — indicating operational stability.
- Overall: Summer and year-end months are most delay-prone due to high travel and weather disruptions.



Model Performance

Classification Model (Delayed or Not): XGBoost Classifier Model is fitting best

- Accuracy: 96.88%

Regression Model (Minutes of avg_delay_per_delayed_flight):XGBoost regressor Model is fitting best

- MAE: 15.76 minutes (After removing large Outliers)
- RMSE: 24.12 minutes
- R2 Score: 37.3%

By SHAPscore we can say that arr_flightsHeavily influences predictions

suggests that arrival traffic volume at the airport is a major factor in predicting delays. Likely correlated with congestion.

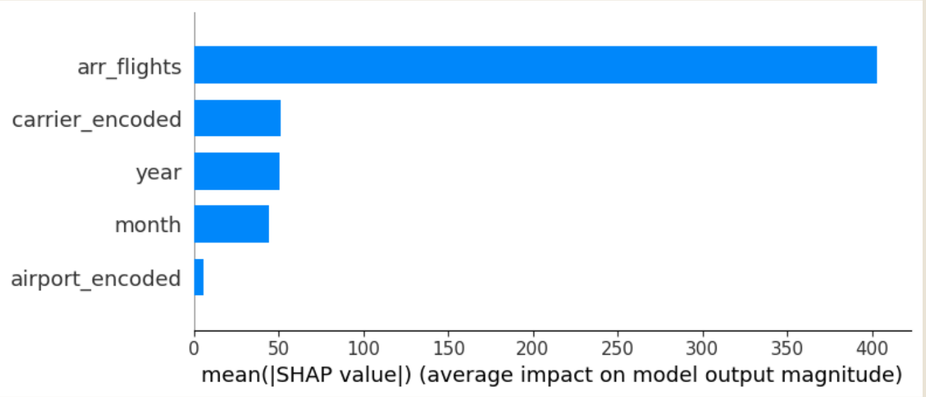
XGBoost Classifier Report:

	precision	recall	f1-score	support
0	0.75	0.50	0.60	1675
1	0.98	0.99	0.98	34075
accuracy			0.97	35750
macro avg	0.86	0.75	0.79	35750
weighted avg	0.97	0.97	0.97	35750

Confusion Matrix:
[[836 839]
[276 33799]]
✅ Accuracy: 96.88 %

Model Comparison Table

Model	MAE	RMSE	R^2
Linear Regression	21.12	30.22	0.016
Random Forest	16.58	25.06	0.323
XGBoost	15.76	24.12	0.373



Actionable Recommendation

1. Reduce Late Aircraft Turnaround Delays (Top Cause - ~39%)
    - Implement buffer times between flight arrivals and departures to absorb minor delays.
    - Improve gate allocation and ground operations to ensure faster turnaround.
2. Optimize Airline Internal Processes (Carrier Delays - ~34%))
    - Enhance crew scheduling systems to reduce unavailability.
    - Standardize maintenance procedures and reduce downtime via ML-based failure prediction.
3. Upgrade Air Traffic and NAS Coordination (NAS Delays - ~21%))
    - Collaborate with ATC authorities to optimize slot allocations and reduce congestion.
    - Invest in smarter scheduling during high-traffic months (May–August).
4. Seasonal Demand Management)
    - Increase staffing and fleet readiness during peak summer and holiday months.
    - Use historical delay trends to anticipate and mitigate seasonal congestion.
5. Resource Allocation:
    - Use SHAP scores + OAI to prioritize operational control efforts.

Thank **you!**