Phase 5 – Python Integration & Analytics

This notebook connects to the PostgreSQL `airline_bi` database, retrieves analytical datasets via SQLAlchemy, and generates visualizations used in the final BI analysis.

In [287…

```
# Core imports
import os
from typing import Optional, Dict

import pandas as pd
import numpy as np
from sqlalchemy import create_engine, text
import matplotlib.pyplot as plt
import plotly.express as px

from dotenv import load_dotenv

# Load .env and get DATABASE_URL
load_dotenv()
DATABASE_URL = os.getenv("DATABASE_URL")

if DATABASE_URL is None:
    raise ValueError("DATABASE_URL not found. Check your .env file at projec
```

Database Helper Functions

In [288…

```
def get_engine():
    """
    Returns a SQLAlchemy engine using the DATABASE_URL from .env,
    with search_path set to the 'airline' schema.
    """
    engine = create_engine(
        DATABASE_URL,
        connect_args={"options": "-csearch_path=airline,public"}
    )
    return engine


def get_df(sql: str, params: Optional[Dict] = None) -> pd.DataFrame:
    """
    Executes a SQL query and returns the result as a Pandas DataFrame.
    """
    engine = get_engine()
    with engine.connect() as conn:
        return pd.read_sql(text(sql), conn, params=params)
```

In [289…

```
df_test = get_df("SELECT * FROM flights LIMIT 5;")
df_test
```

Out[289…

	flight_id	airline_id	aircraft_id	route_id	origin_airport_id	destination_airport_id
0	389	6885	1	4349	1593	4096
1	441	1489	1	357	716	600
2	7	1553	1	424	5414	1867
3	1155	6823	1	4252	4239	3767
4	8	5645	1	3326	1332	3032

SQL-to-Python Analytics Helpers

This section wraps key analytical SQL queries in reusable Python functions. Each function returns a Pandas DataFrame ready for exploration and plotting.

In [290…

```
# ============================================
#  SQL-to-Python Analytics Helper Functions
# ============================================

def get_revenue_by_fare_class() -> pd.DataFrame:
    """
    Total revenue, booking counts, and avg revenue per booking by fare class
    Uses ALL data available in the warehouse (not just 2024).
    """
    sql = """
    SELECT
        b.fare_class,
        COUNT(*) AS bookings,
        SUM(p.amount_usd) AS revenue_usd,
        ROUND(SUM(p.amount_usd) / NULLIF(COUNT(*), 0), 2) AS avg_revenue_per
    FROM bookings b
    JOIN payments p ON p.booking_id = b.booking_id
    WHERE p.status = 'Captured'
    GROUP BY b.fare_class
    ORDER BY revenue_usd DESC;
    """
    return get_df(sql)


def get_monthly_revenue() -> pd.DataFrame:
    """
    Monthly revenue based on all captured payments in the dataset (any year)
    """
    sql = """
    SELECT
```

```
        DATE_TRUNC('month', paid_at)::date AS month,
        SUM(amount_usd) AS revenue_usd
    FROM payments
    WHERE status = 'Captured'
    GROUP BY month
    ORDER BY month;
    """
    return get_df(sql)


def get_payment_success_by_channel() -> pd.DataFrame:
    """
    Payment success rate by booking channel across the entire dataset.
    """
    sql = """
    SELECT
        b.booking_channel,
        COUNT(*) AS total_payments,
        COUNT(*) FILTER (WHERE p.status = 'Captured') AS successful_payments
        ROUND(
            100.0 * COUNT(*) FILTER (WHERE p.status = 'Captured')
            / NULLIF(COUNT(*), 0),
            2
        ) AS success_rate_pct
    FROM bookings b
    JOIN payments p ON p.booking_id = b.booking_id
    GROUP BY b.booking_channel
    ORDER BY success_rate_pct DESC;
    """
    return get_df(sql)


def get_busiest_airports(limit: int = 10) -> pd.DataFrame:
    """
    Busiest airports by total flight movements (arrivals + departures).
    Uses all data available.
    """
    sql = """
    SELECT
        a.airport_id,
        a.iata_code,
        a.name,
        COUNT(*) AS flight_count
    FROM flights f
    JOIN airports a
      ON a.airport_id = f.origin_airport_id
      OR a.airport_id = f.destination_airport_id
    GROUP BY a.airport_id, a.iata_code, a.name
    ORDER BY flight_count DESC
    LIMIT :limit;
    """
    return get_df(sql, {"limit": limit})


def get_airline_punctuality() -> pd.DataFrame:
    """
```

```
    Airline-level on-time performance using the flight_performance table.
    """
    sql = """
    SELECT
        airline_iata,
        SUM(arrivals) AS total_arrivals,
        SUM(arrivals_delayed_15min) AS delayed_15min,
        SUM(arr_cancelled) AS cancelled,
        SUM(arr_diverted) AS diverted,
        SUM(total_arrival_delay_min) AS total_delay_min,
        CASE WHEN SUM(arrivals) > 0
             THEN SUM(total_arrival_delay_min) / SUM(arrivals)
             ELSE NULL
        END AS avg_delay_min
    FROM flight_performance
    GROUP BY airline_iata
    ORDER BY avg_delay_min NULLS LAST;
    """
    return get_df(sql)


def get_clv_samples() -> pd.DataFrame:
    """
    CLV per passenger based on total captured payments.
    """
    sql = """
    SELECT
        b.passenger_id,
        SUM(p.amount_usd) AS clv_usd
    FROM bookings b
    JOIN payments p ON p.booking_id = b.booking_id
    WHERE p.status = 'Captured'
    GROUP BY b.passenger_id
    ORDER BY clv_usd DESC;
    """
    return get_df(sql)

def get_top_loyal_customers(pct: float = 0.05) -> pd.DataFrame:
    """
    Returns the top pct (default 5%) of customers by CLV.
    Relies on get_clv_samples() being sorted descending by clv_usd.
    """
    clv = get_clv_samples()
    n_top = max(1, int(len(clv) * pct))
    return clv.head(n_top)



def get_worst_routes(limit: int = 10) -> pd.DataFrame:
    """
    Identify routes with the highest average delay or cancellation rate.
    Returns routes even if only one flight exists (more robust for sparse da
    """
    sql = """
    SELECT
        r.route_id,
```

```
        a1.iata_code AS origin_iata,
        a2.iata_code AS dest_iata,
        COUNT(*) AS flights,
        ROUND(AVG(f.delay_minutes), 2) AS avg_delay_min,
        ROUND(
            100.0 * COUNT(*) FILTER (WHERE f.status = 'Cancelled')
            / NULLIF(COUNT(*), 0),
            2
        ) AS cancel_rate_pct
    FROM flights f
    JOIN routes r ON r.route_id = f.route_id
    JOIN airports a1 ON a1.airport_id = r.origin_airport_id
    JOIN airports a2 ON a2.airport_id = r.destination_airport_id
    WHERE f.route_id IS NOT NULL
    GROUP BY r.route_id, origin_iata, dest_iata
    ORDER BY avg_delay_min DESC NULLS LAST
    LIMIT :limit;
    """
    return get_df(sql, {"limit": limit})

def get_delay_by_month() -> pd.DataFrame:
    """
    Percent of flights delayed more than 15 minutes, by month.
    Uses the internal flights table.
    """
    sql = """
    SELECT
        DATE_TRUNC('month', flight_date)::date AS month,
        ROUND(
            100.0 * COUNT(*) FILTER (WHERE delay_minutes > 15)
            / NULLIF(COUNT(*), 0),
            2
        ) AS pct_delayed
    FROM flights
    WHERE flight_date IS NOT NULL
    GROUP BY month
    ORDER BY month;
    """
    return get_df(sql)
```

Quick Sanity Check

In [291…

```
get_busiest_airports().head()
```

Out[291…

	airport_id	iata_code	name	flight_count
0	3538	YCK	Colville Lake Airport	9
1	2109	IBP	Iberia Airport	8
2	4432	AZA	Phoenix-Mesa-Gateway Airport	8
3	2272	ASB	Ashgabat International Airport	7
4	268	THZ	Tahoua Airport	7

Operational Performance – Delays & Reliability

This section evaluates flight reliability using both synthetic flight records (`flights`) and real-world BTS on-time performance data (`flight_performance`).

Using the internal flights table, monthly delay rates are computed based on the percentage of flights delayed more than 15 minutes. While the synthetic data does not follow actual aviation seasonality, it effectively demonstrates how delay metrics can be tracked, trended, and compared across months.

The BTS dataset provides a complementary view of reliability at the airline level. Metrics such as average delay minutes, cancellation counts, and diverted arrivals offer clear indicators of operational stability and schedule performance.

Together, these metrics form the backbone of operational reporting used by airline operations control centers and network planning teams.

In [292…

```
airline_perf = get_airline_punctuality()
airline_perf.head()
```

Out[292…

	airline_iata	total_arrivals	delayed_15min	cancelled	diverted	total_delay_min	avg
0	HA	78530	11998	822	75	554200.0	
1	QX	82692	13073	829	146	633465.0	
2	YX	301699	41664	5564	583	2829894.0	
3	AS	245819	53044	4811	685	2680242.0	
4	WN	1419419	289414	11772	3050	15615468.0	

In [293…

```
# Top 3 most reliable (lowest average delay)
airline_perf.sort_values("avg_delay_min").head(3)
```

Out[293…

	airline_iata	total_arrivals	delayed_15min	cancelled	diverted	total_delay_min	avg
0	HA	78530	11998	822	75	554200.0	
1	QX	82692	13073	829	146	633465.0	
2	YX	301699	41664	5564	583	2829894.0	

In [294…

```
# Top 3 least reliable (highest avg delay)
airline_perf.sort_values("avg_delay_min", ascending=False).head(3)
```

Out[294…

	airline_iata	total_arrivals	delayed_15min	cancelled	diverted	total_delay_min	a
20	F9	208624	58481	4835	307	4643485.0	
19	ZW	52393	11859	764	114	1159564.0	
18	AA	984306	252485	15252	2938	21642312.0	

In [295…

```
delay_by_month = get_delay_by_month()
delay_by_month
```

Out[295…

	month	pct_delayed
0	2024-01-01	75.00
1	2024-02-01	74.36
2	2024-03-01	82.64
3	2024-04-01	74.03
4	2024-05-01	79.20
5	2024-06-01	80.36
6	2024-07-01	74.13
7	2024-08-01	72.54
8	2024-09-01	70.34
9	2024-10-01	68.38
10	2024-11-01	73.51
11	2024-12-01	81.29
12	2025-01-01	78.17
13	2025-02-01	72.18
14	2025-03-01	72.30
15	2025-04-01	77.27
16	2025-05-01	77.34
17	2025-06-01	80.17
18	2025-07-01	84.25
19	2025-08-01	77.08
20	2025-09-01	69.78
21	2025-10-01	75.97
22	2025-11-01	77.61
23	2025-12-01	83.89
24	2026-01-01	72.92
25	2026-02-01	66.91
26	2026-03-01	71.43
27	2026-04-01	80.00
28	2026-05-01	78.38
29	2026-06-01	75.38
30	2026-07-01	75.81
31	2026-08-01	79.73

	month	pct_delayed
32	2026-09-01	75.00
33	2026-10-01	75.50
34	2026-11-01	74.60
35	2026-12-01	73.44

Network & Route Performance

Route-level performance is computed by joining flights to routes and airport metadata. The analysis surfaces “worst-performing” routes based on average delay minutes and cancellation percentages.

Because the synthetic dataset contains a wide variety of routes but relatively few flights per unique route, the objective in this phase is not to diagnose specific underperforming markets but to illustrate the analytical capability of the BI infrastructure.

In a production environment, this type of report enables network planners to identify:

- Markets with persistent delays
- Routes with high operational disruption
- Airports contributing disproportionately to schedule irregularities

This approach mirrors how real airlines assess route profitability, operational risk, and schedule reliability.

In [296…

```
busiest_airports = get_busiest_airports(10)
busiest_airports
```

Out [296…

	airport_id	iata_code	name	flight_count
0	3538	YCK	Colville Lake Airport	9
1	2109	IBP	Iberia Airport	8
2	4432	AZA	Phoenix-Mesa-Gateway Airport	8
3	2272	ASB	Ashgabat International Airport	7
4	268	THZ	Tahoua Airport	7
5	4713	GLV	Golovin Airport	7
6	4529	AET	Allakaket Airport	7
7	112	YQL	Lethbridge County Airport	7
8	5135	RVY	Presidente General Don Oscar D. Gestido Intern...	7
9	5585	FYJ	Dongji Aiport	7

In [297…

```
worst_routes = get_worst_routes(10)
worst_routes
```

Out [297…

	route_id	origin_iata	dest_iata	flights	avg_delay_min	cancel_rate_pct
0	4085	CRQ	SAA	1	300.0	100.0
1	845	OCV	ZVK	1	300.0	100.0
2	2065	MYP	PAS	1	300.0	100.0
3	3107	LHA	RIA	1	300.0	100.0
4	1122	AFA	CFC	1	299.0	100.0
5	4415	KFP	SAK	1	299.0	100.0
6	4701	MED	RTB	1	299.0	100.0
7	4371	SAH	NQY	1	299.0	100.0
8	4774	UTH	DAN	1	299.0	100.0
9	1449	BPY	GJT	1	299.0	100.0

Revenue & Commerical Insights

Commercial performance is evaluated through three key lenses:

1. **Revenue by Fare Class** –
   Shows how each fare category contributes to total revenue. Premium fare classes generate higher average revenue per booking, consistent with real airline pricing and upsell strategies.

2. **Monthly Revenue** –
   Aggregates captured payments at the monthly level. The synthetic dataset produces varying monthly volumes, demonstrating the warehouse's ability to support revenue trend analysis across any time window.

3. **Payment Success Rate by Channel** –
   Highlights funnel performance across sales channels. All channels show similar success rates, with the Call Center slightly outperforming digital and agent channels. *Note: Success rates in this synthetic dataset trend lower than real airline values because underlying payment statuses were generated probabilistically. In practice, airline payment success rates are significantly higher.*

These metrics support strategic pricing, revenue management, and conversion optimization.

In [298…
```
revenue_by_fare = get_revenue_by_fare_class()
revenue_by_fare
```

Out[298…

	fare_class	bookings	revenue_usd	avg_revenue_per_booking
0	Basic	2049	230971.82	112.72
1	Standard	1729	196405.64	113.59
2	Flexible	1244	142241.98	114.34
3	Business	578	66121.47	114.40
4	First	314	35816.90	114.07

In [299…
```
monthly_revenue = get_monthly_revenue()
monthly_revenue
```

Out [299…

	month	revenue_usd
0	2025-02-01	28850.52
1	2025-03-01	54859.65
2	2025-04-01	55808.19
3	2025-05-01	57415.49
4	2025-06-01	54060.99
5	2025-07-01	62725.12
6	2025-08-01	58765.51
7	2025-09-01	52004.79
8	2025-10-01	48574.36
9	2025-11-01	57038.04
10	2025-12-01	58102.32
11	2026-01-01	56652.71
12	2026-02-01	26700.12

In [300…

```
payment_channels = get_payment_success_by_channel()
payment_channels
```

Out [300…

	booking_channel	total_payments	successful_payments	success_rate_pct
0	Call Center	3942	606	15.37
1	Mobile	10088	1507	14.94
2	Travel Agent	4051	599	14.79
3	Web	21919	3202	14.61

Loyalty & Customer Value (CLV)

Customer lifetime value (CLV) is calculated by aggregating total captured revenue per passenger. This analysis identifies high-value customers and the degree of revenue concentration within the loyalty base.

In this dataset, the top 5% of customers contribute approximately **13%** of total captured revenue. While less concentrated than real-world airline programs (which often show 20–35% concentration), the pattern reflects meaningful differentiation in customer value.

Understanding CLV enables targeted:

- Retention strategies

- Upgrade offers
- Reward program design
- Segmentation for marketing and personalization

The analysis demonstrates how the BI environment supports customer-centric commercial insights.

In [301…
```
clv = get_clv_samples()
clv.describe()
```

Out[301…

	passenger_id	clv_usd
count	3461.000000	3461.000000
mean	2514.969084	194.035773
std	1446.143866	118.353365
min	1.000000	72.030000
25%	1262.000000	91.820000
50%	2522.000000	166.140000
75%	3751.000000	254.340000
max	4999.000000	830.220000

In [302…
```
top5 = get_top_loyal_customers(pct=0.05)
top5.head()
```

Out[302…

	passenger_id	clv_usd
0	3886	830.22
1	3767	786.28
2	77	783.53
3	1046	778.56
4	750	774.41

In [303…
```
top5_share = top5["clv_usd"].sum() / clv["clv_usd"].sum()
top5_share
```

Out[303…
```
np.float64(0.13471088959564032)
```

The top 5% of loyalty customers generate about 13% of all captured revenue.

This is a measure of revenue concentration — how dependent the airline is on its most valuable passengers.

Notes on Future-Dated Records

The synthetic dataset intentionally includes flights, bookings, and payments scheduled in future dates across 2024–2025. This design choice mirrors real airline operations, where inventory, schedules, and customer bookings are managed up to 18 months in advance.

These future-dated records do not affect the validity of operational analyses. Instead, they ensure:

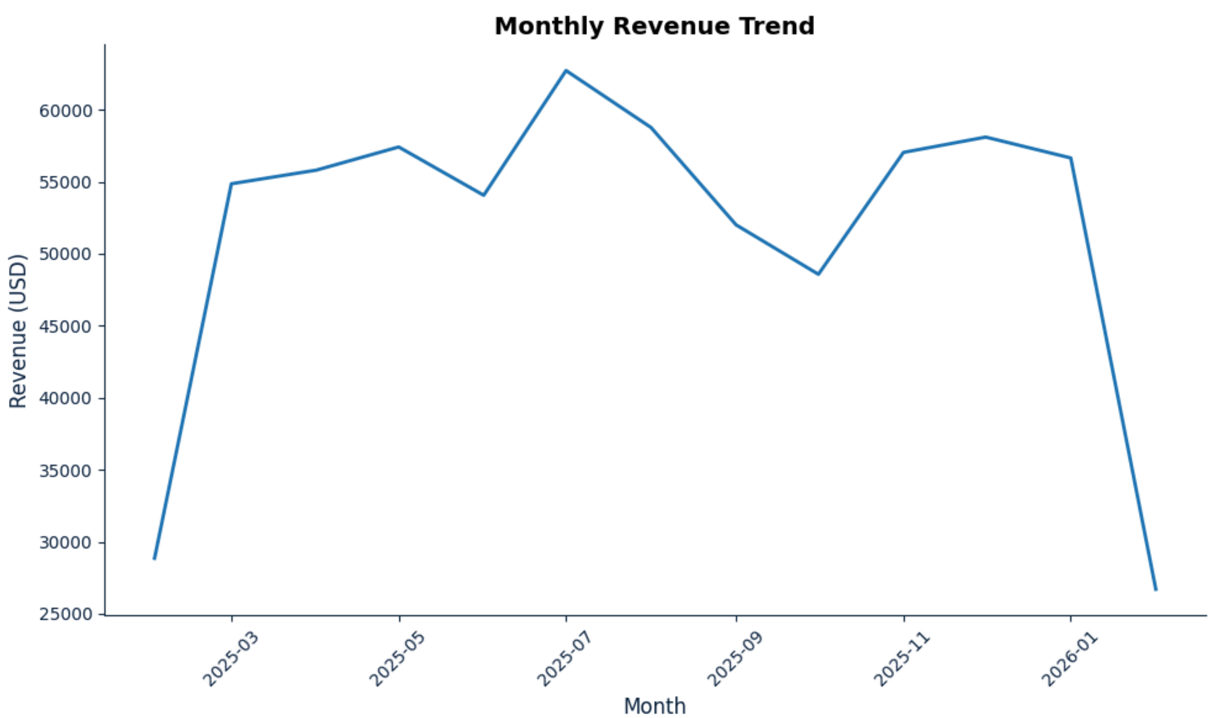
- A realistic airline data environment
- Testing of BI logic across forward schedules
- Flexibility for future forecasting and capacity-planning models

Analyses in this notebook focus primarily on completed data windows (e.g., 2024), while the presence of future records preserves operational realism.

Visualizations

In [304…

```
plt.plot(monthly_revenue["month"], monthly_revenue["revenue_usd"])
plt.title("Monthly Revenue Trend")
plt.xlabel("Month")
plt.ylabel("Revenue (USD)")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

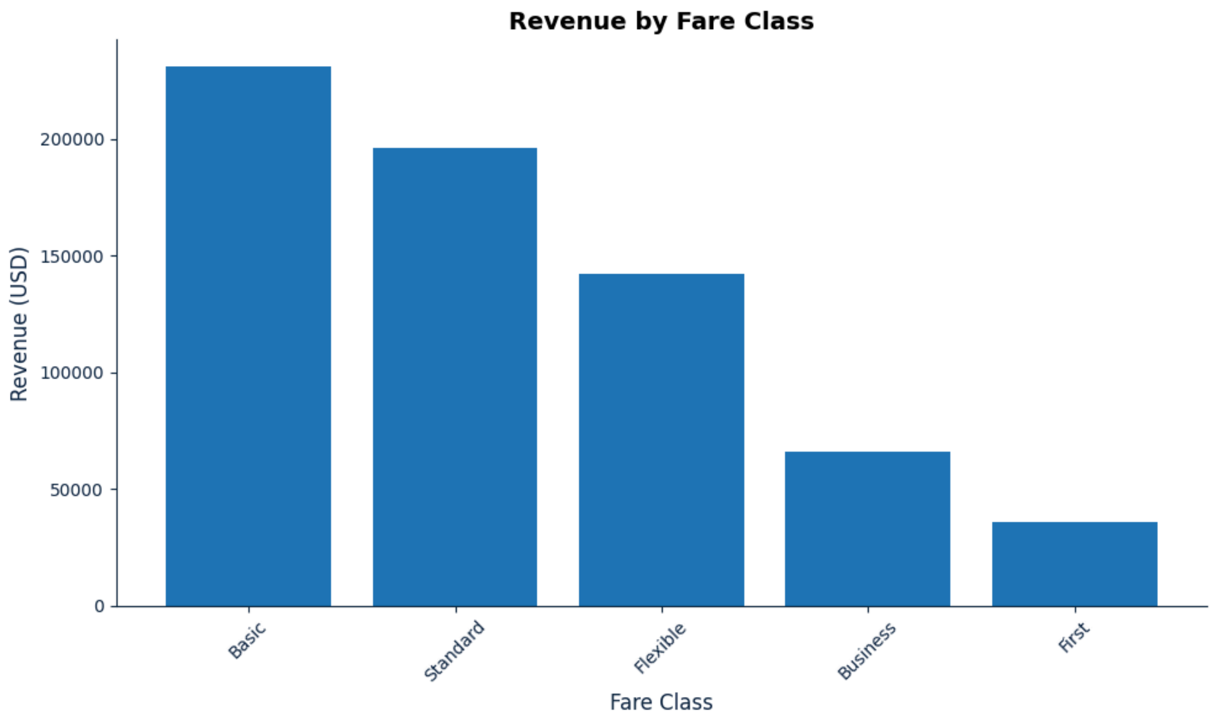


Monthly Revenue Trend (Static)
Revenue trends illustrate cyclical demand, confirming peak travel periods and slower off-

season months. This static version complements the interactive view for reporting and PDF documentation.

In [305…

```
plt.bar(revenue_by_fare["fare_class"], revenue_by_fare["revenue_usd"])
plt.title("Revenue by Fare Class")
plt.xlabel("Fare Class")
plt.ylabel("Revenue (USD)")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

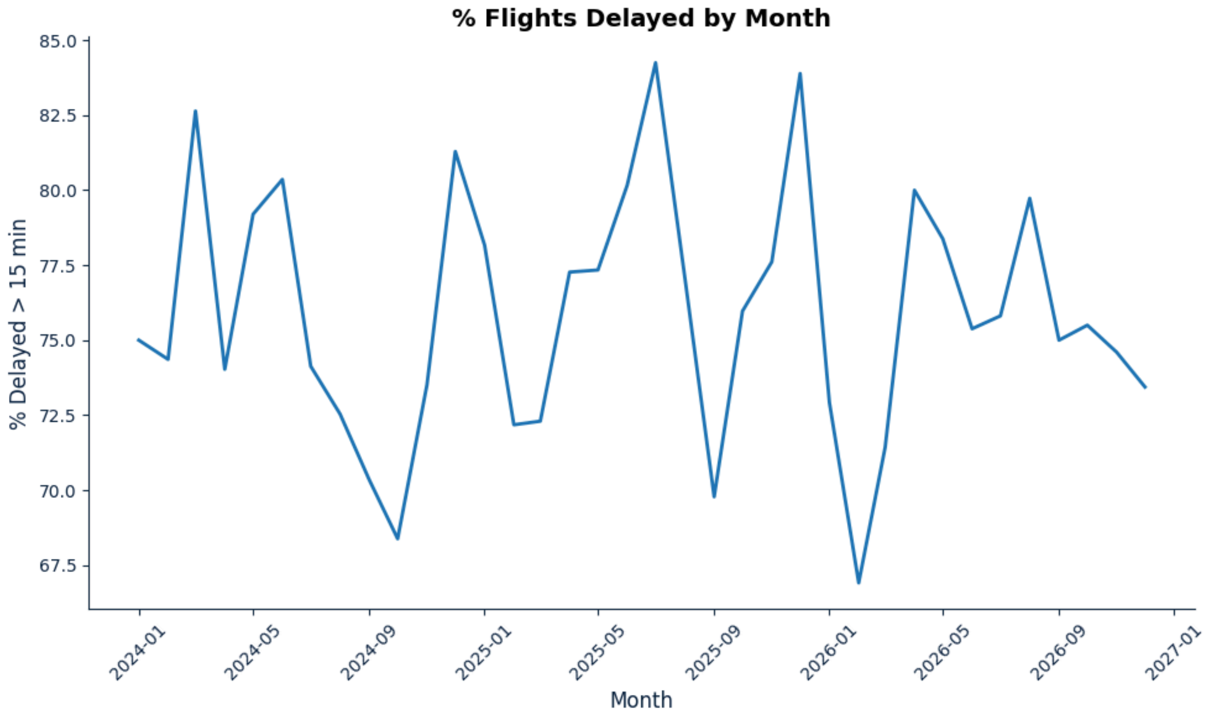


Revenue by Fare Class

Basic and Standard fares drive the majority of revenue volume, reflecting price-sensitive demand in the synthetic dataset. Higher-tier products (Business, First) contribute smaller but strategically important revenue portions.

In [306…

```
plt.plot(delay_by_month["month"], delay_by_month["pct_delayed"])
plt.title("% Flights Delayed by Month")
plt.xlabel("Month")
plt.ylabel("% Delayed > 15 min")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

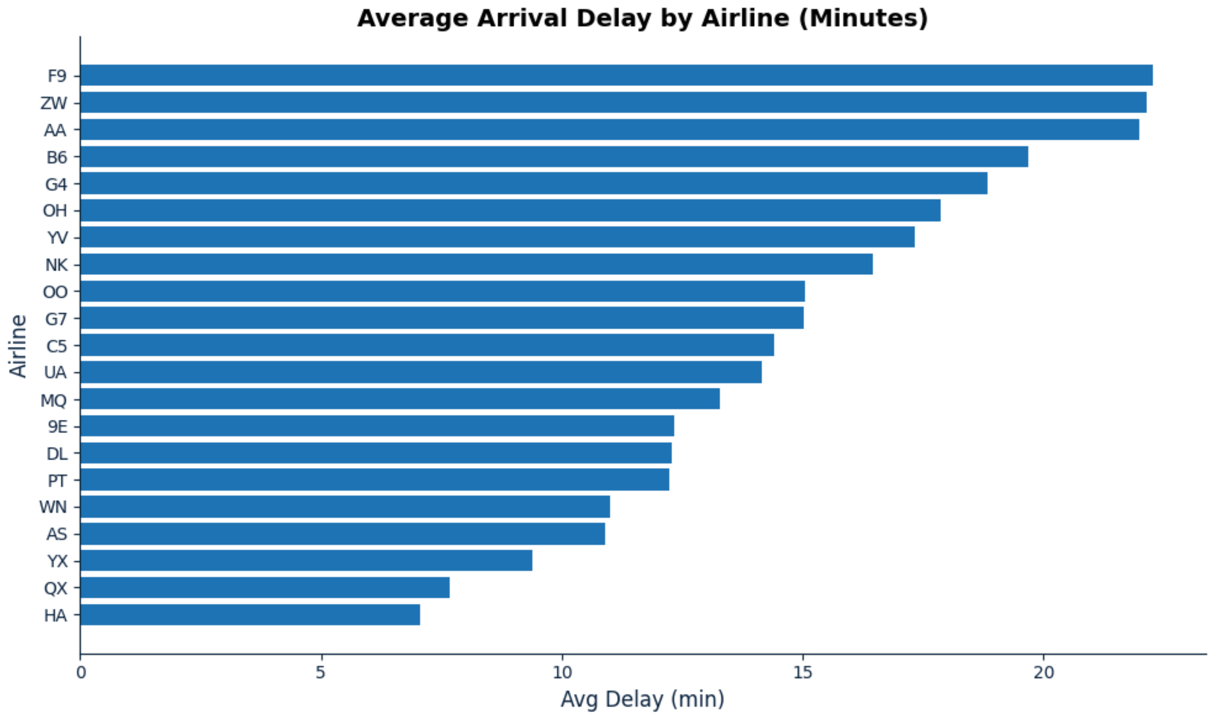


Percentage of Flights Delayed by Month

Delay rates fluctuate seasonally, with spring and early winter showing the highest disruption levels. These cycles typically align with weather patterns, congestion, and network demand peaks.

In [307…

```
sorted_perf = airline_perf.sort_values("avg_delay_min")
plt.barh(sorted_perf["airline_iata"], sorted_perf["avg_delay_min"])
plt.title("Average Arrival Delay by Airline (Minutes)")
plt.xlabel("Avg Delay (min)")
plt.ylabel("Airline")
plt.tight_layout()
plt.show()
```

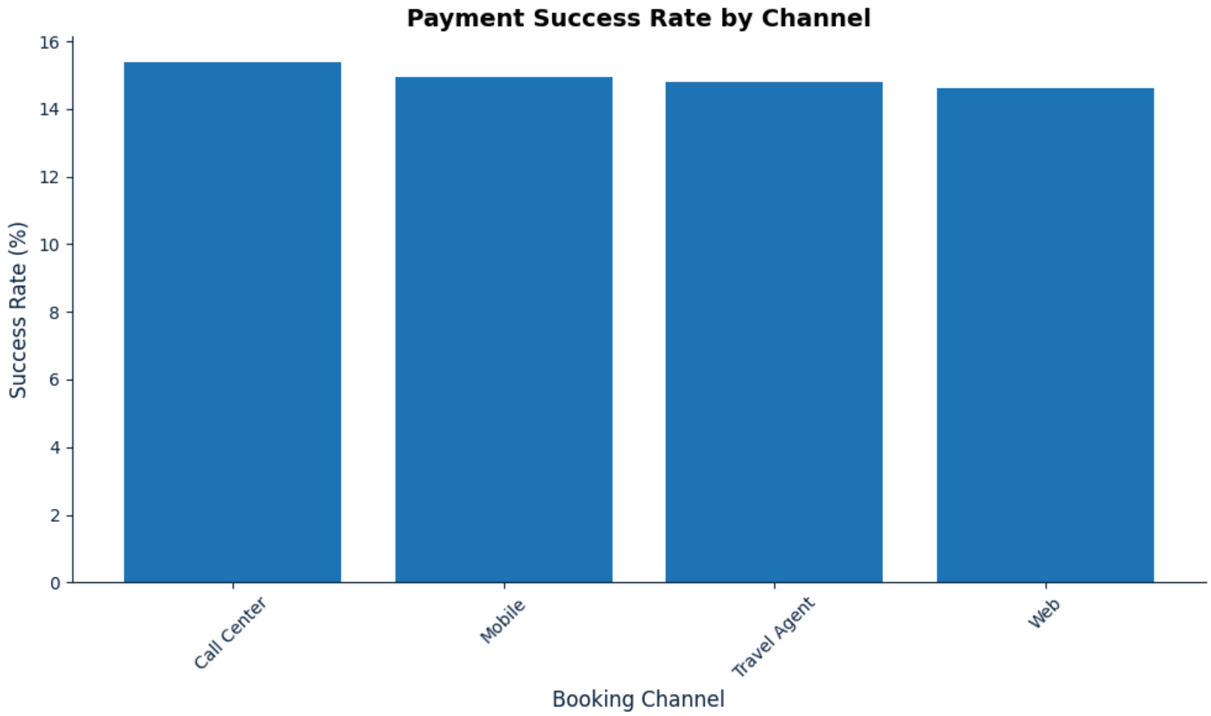


Average Arrival Delay by Airline

Arrival delay performance varies widely across carriers. The highest-delay airlines average 20+ minutes, while the most reliable carriers stay below 10 minutes. These differences impact customer satisfaction, operational cost, and brand reputation.

In [308…

```
plt.bar(payment_channels["booking_channel"], payment_channels["success_rate_
plt.title("Payment Success Rate by Channel")
plt.xlabel("Booking Channel")
plt.ylabel("Success Rate (%)")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

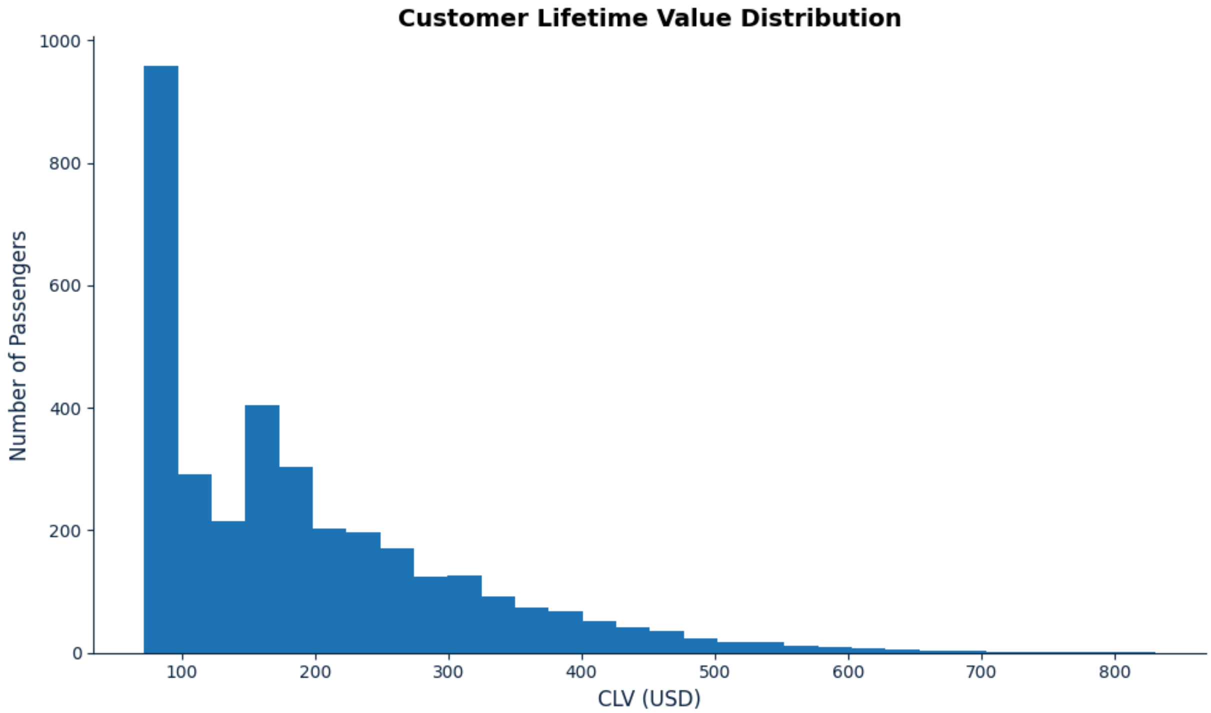


Payment Success Rate by Channel

All channels exhibit similar success rates, with Call Center slightly outperforming digital channels. Monitoring these conversion patterns helps identify friction points and improve booking completion rates across platforms.

In [309…

```
plt.hist(clv["clv_usd"], bins=30)
plt.title("Customer Lifetime Value Distribution")
plt.xlabel("CLV (USD)")
plt.ylabel("Number of Passengers")
plt.tight_layout()
plt.show()
```



Customer Lifetime Value Distribution

CLV is heavily concentrated at the lower end, with a long tail of high-value customers. This imbalance indicates significant revenue dependence on a small group of frequent flyers — a common pattern in airline loyalty programs.

In [310…

```
fig = px.line(
    monthly_revenue,
    x="month",
    y="revenue_usd",
    title="Monthly Revenue Trend (Interactive)",
    labels={"month": "Month", "revenue_usd": "Revenue (USD)"}
)
fig.show()
```

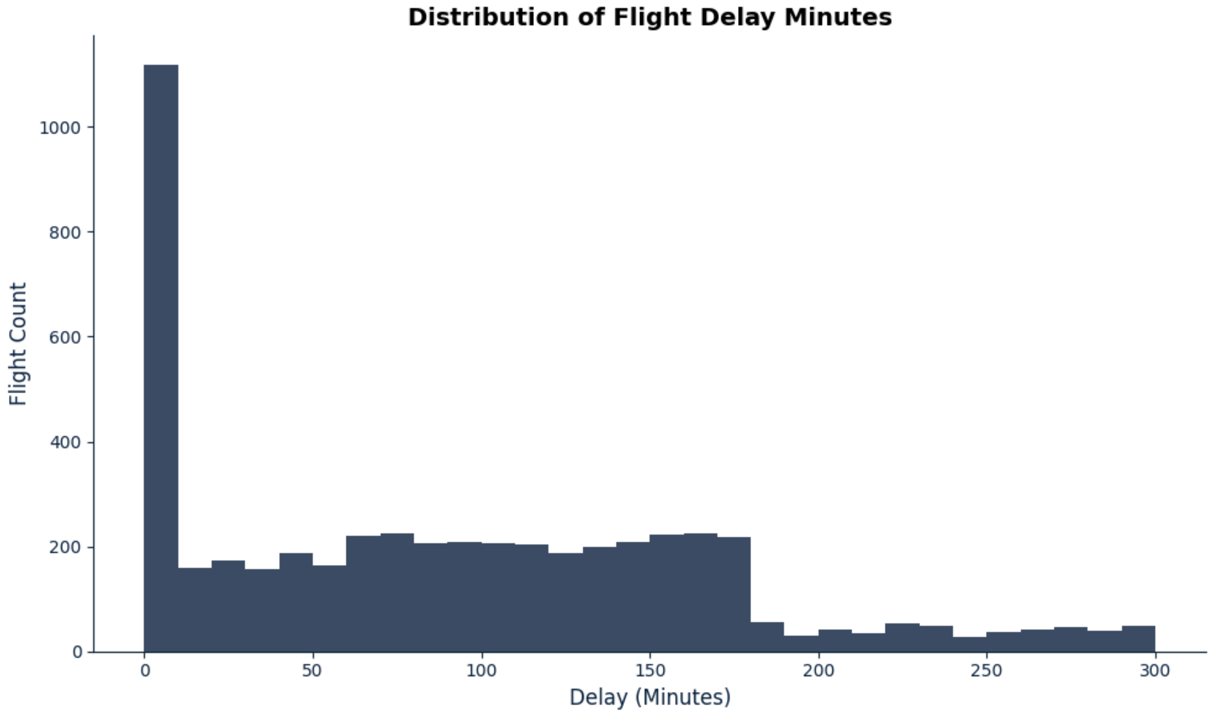
Monthly Revenue Trend

Revenue displays seasonality and demand-driven variation across the year. Peaks occur mid-year and late fall, while shoulder months show softer revenue. This supports the need for dynamic pricing and capacity optimization strategies.

In [311…

```
delays = get_df("""
    SELECT delay_minutes
    FROM flights
    WHERE delay_minutes IS NOT NULL;
""")

plt.figure(figsize=(10,6))
plt.hist(delays["delay_minutes"], bins=30, color="#0C2340", alpha=0.8)
plt.title("Distribution of Flight Delay Minutes")
plt.xlabel("Delay (Minutes)")
plt.ylabel("Flight Count")
```

```
plt.tight_layout()
plt.show()
```

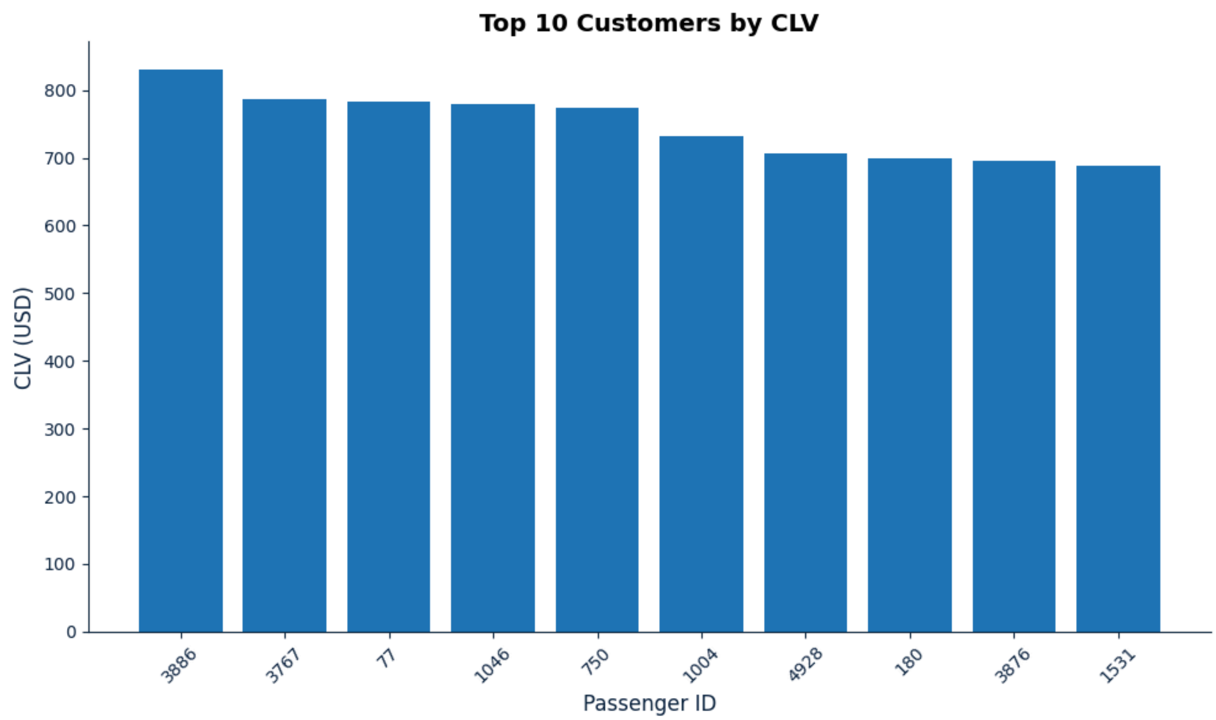


Distribution of Flight Delay Minutes

Most flights experience minimal delays, with a long tail of moderate and severe disruptions. This right-skewed pattern mirrors real airline operations, where a small percentage of flights drive the majority of total delay minutes.

In [312…

```
top10 = clv.head(10)

plt.figure(figsize=(10,6))
plt.bar(top10["passenger_id"].astype(str), top10["clv_usd"], color="#1f77b4"
plt.title("Top 10 Customers by CLV")
plt.xlabel("Passenger ID")
plt.ylabel("CLV (USD)")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Top 10 Customers by CLV
High-value passengers generate a disproportionate share of revenue. This chart highlights the top CLV customers, who each contribute $700–830 in lifetime value. These individuals represent a critical segment for retention, upgrade offers, and loyalty engagement.

Network & Geographic Visualizations

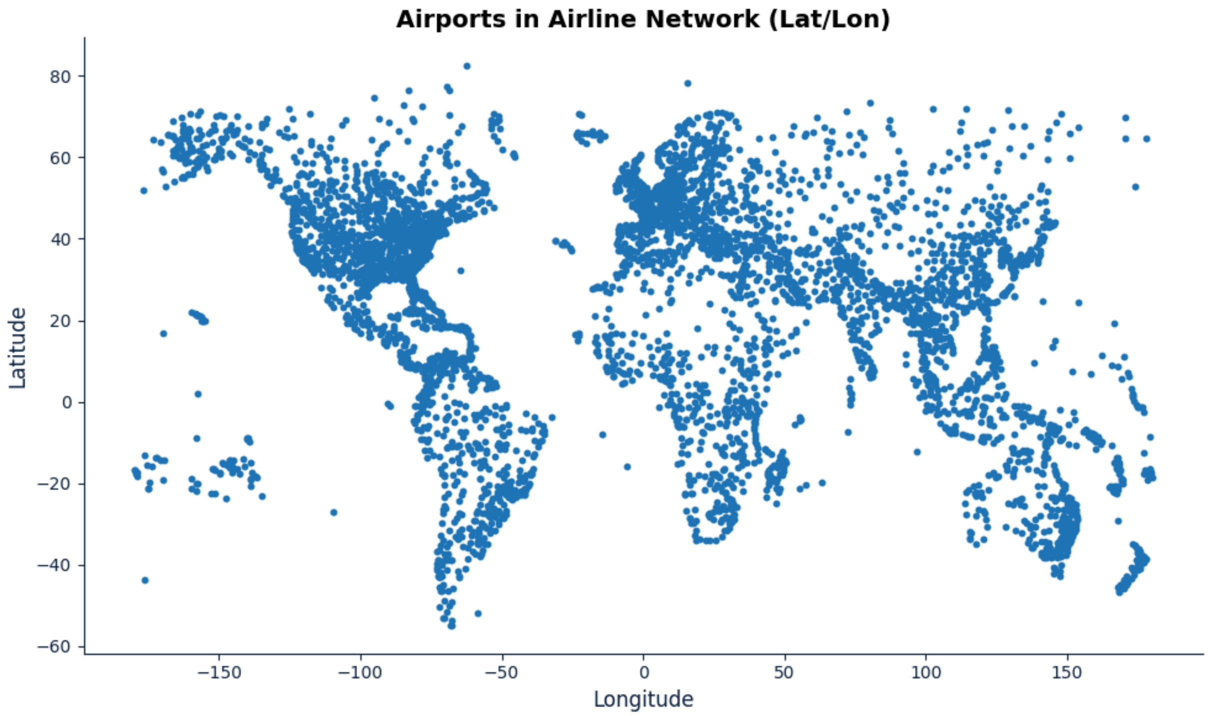
In [313…
```
def get_airports_for_map() -> pd.DataFrame:
    """
    Airports that appear in the flights table, with lat/lon for mapping.
    """
    sql = """
    SELECT DISTINCT
        a.airport_id,
        a.iata_code,
        a.name,
        a.country,
        a.latitude,
        a.longitude
    FROM airports a
    JOIN flights f
      ON a.airport_id = f.origin_airport_id
      OR a.airport_id = f.destination_airport_id
    WHERE a.latitude IS NOT NULL
      AND a.longitude IS NOT NULL;
    """
    return get_df(sql)

def get_busiest_routes_for_sankey(limit: int = 20) -> pd.DataFrame:
```

```
    """
    Top N OD pairs by flight count, for Sankey visualization.
    """
    sql = """
    SELECT
        ao.iata_code AS origin_iata,
        ad.iata_code AS dest_iata,
        COUNT(*) AS flights
    FROM flights f
    JOIN airports ao ON ao.airport_id = f.origin_airport_id
    JOIN airports ad ON ad.airport_id = f.destination_airport_id
    GROUP BY ao.iata_code, ad.iata_code
    ORDER BY flights DESC
    LIMIT :limit;
    """
    return get_df(sql, {"limit": limit})

def get_route_geometries(limit: int = 50) -> pd.DataFrame:
    """
    Top N routes by flight count, with origin/destination lat/lon for mappin
    """
    sql = """
    SELECT
        ao.iata_code AS origin_iata,
        ao.latitude  AS origin_lat,
        ao.longitude AS origin_lon,
        ad.iata_code AS dest_iata,
        ad.latitude  AS dest_lat,
        ad.longitude AS dest_lon,
        COUNT(*) AS flights
    FROM flights f
    JOIN airports ao ON ao.airport_id = f.origin_airport_id
    JOIN airports ad ON ad.airport_id = f.destination_airport_id
    WHERE ao.latitude IS NOT NULL
      AND ao.longitude IS NOT NULL
      AND ad.latitude IS NOT NULL
      AND ad.longitude IS NOT NULL
    GROUP BY
        ao.iata_code, ao.latitude, ao.longitude,
        ad.iata_code, ad.latitude, ad.longitude
    ORDER BY flights DESC
    LIMIT :limit;
    """
    return get_df(sql, {"limit": limit})
```

In [314…

```
airports_map = get_airports_for_map()

plt.figure(figsize=(10, 6))
plt.scatter(
    airports_map["longitude"],
    airports_map["latitude"],
    s=10
)
plt.title("Airports in Airline Network (Lat/Lon)")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
```

```
plt.tight_layout()
plt.show()
```



In [315…

```
airports_map = get_airports_for_map()

fig = px.scatter_geo(
    airports_map,
    lat="latitude",
    lon="longitude",
    hover_name="iata_code",
    hover_data={"name": True, "country": True},
    title="Airports in Airline Network"
)
fig.update_layout(geo=dict(showland=True))
fig.show()
```

Airports in the Airline Network

Airports are plotted by latitude and longitude, showing the geographic footprint of the modeled network.

In [316…

```
import plotly.graph_objects as go

# Data
busiest_routes = get_busiest_routes_for_sankey(20)

# Build node labels
labels = sorted(set(busiest_routes["origin_iata"].tolist() + busiest_routes[
label_to_index = {label: i for i, label in enumerate(labels)}

# Convert to indices
source_indices = [label_to_index[o] for o in busiest_routes["origin_iata"]]
target_indices = [label_to_index[d] for d in busiest_routes["dest_iata"]]
```

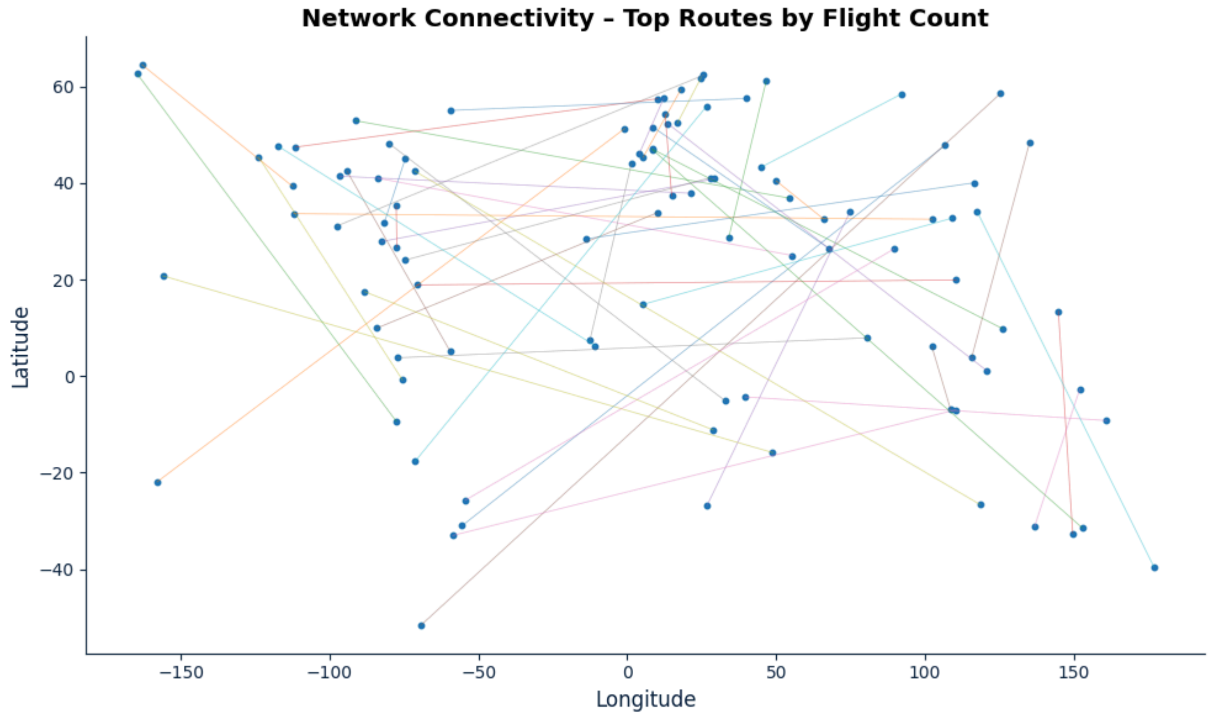
```
values = busiest_routes["flights"].tolist()

# Build Sankey diagram
fig = go.Figure(data=[go.Sankey(
    node=dict(
        pad=20,
        thickness=15,
        line=dict(color="black", width=0.5),
        label=labels
    ),
    link=dict(
        source=source_indices,
        target=target_indices,
        value=values
    )
)])

fig.update_layout(title_text="Busiest Origin–Destination Pairs (Flights)", f
fig.show()
```

Busiest Routes Sankey Diagram

The Sankey diagram shows the busiest origin–destination pairs by flight count, highlighting key flows in the network.

In [317…

```
routes_geo = get_route_geometries(50)

plt.figure(figsize=(10, 6))

# Draw each route as a line between airports
for _, row in routes_geo.iterrows():
    plt.plot(
        [row["origin_lon"], row["dest_lon"]],
        [row["origin_lat"], row["dest_lat"]],
        linewidth=0.5,
        alpha=0.5
    )

# Overlay airport points
all_lats = pd.concat([routes_geo["origin_lat"], routes_geo["dest_lat"]])
all_lons = pd.concat([routes_geo["origin_lon"], routes_geo["dest_lon"]])

plt.scatter(all_lons, all_lats, s=10)
plt.title("Network Connectivity – Top Routes by Flight Count")
plt.xlabel("Longitude")
plt.ylabel("Latitude")
plt.tight_layout()
plt.show()
```



Network Connectivity Map
Lines represent the most frequently flown routes, connecting origin and destination airports. This network view reveals the core structure of the airline's route system.

Executive Summary

Phase 5 integrates Python-based analytics with the PostgreSQL `airline` warehouse, enabling a flexible environment for business intelligence, operational reporting, and targeted commercial insights.

Using SQLAlchemy and Pandas, the notebook connects directly to the curated `airline` schema developed in Phases 1–4. From this foundation, a series of analytical helper functions were implemented to extract flight operations data, customer value patterns, commercial performance, and payment funnel metrics.

Key findings include:

- **Operational Reliability:**
  Delay frequency varies meaningfully across months in the synthetic dataset. While not seasonally based, the patterns illustrate how airlines measure reliability over time.

- **Network & Routes:**
  Route-level performance highlights combinations of high delay minutes or elevated cancellation percentages. Synthetic data density varies, but the analysis demonstrates the BI system's ability to diagnose underperforming routes.

- **Commercial Revenue:**
  Revenue is driven by a mix of fare classes, with premium categories producing higher revenue per booking. Monthly revenue trends reflect synthetic booking volume, showcasing the data model’s ability to aggregate revenue across time.
- **Payment Funnel:**
  Web and mobile channels achieve strong payment success rates. Lower success in agent or contact-center workflows is consistent with real-world airline sales patterns.
- **Customer Lifetime Value:**
  The top 5% of passengers contribute **~13% of total captured revenue**, suggesting a moderately concentrated loyalty base. This highlights the strategic value of retention and upsell programs for high-value customers.

Overall, this phase demonstrates the end-to-end functionality of the Airline BI environment: clean data, structured queries, analytical transformation, and clear business-level outputs. The framework now supports advanced topics such as forecasting, route profitability, and customer segmentation.