✈️ Flight Delay Analytics - Newark Liberty International Airport (EWR)

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📘 Objective

This project analyzes flight delays at Newark Liberty International Airport (EWR) using U.S. Bureau of Transportation Statistics data.
The goal is to identify delay patterns, primary causes and airline performance to provide insights for improving on-time operations.

In [3]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

🔄 In this section, the dataset is loaded, inspected and cleaned. Missing or inconsistent values are handled and data types are verified to prepare the dataset for visualization and analysis.

In [4]:
```
df = pd.read_csv("Airline_Delay_Cause.csv")
df.head

#checking for missing value
df.isnull().sum()
```

Out[4]:
```
year                   0
month                  0
carrier                0
carrier_name           0
airport                0
airport_name           0
arr_flights            0
arr_del15              0
carrier_ct             0
weather_ct             0
nas_ct                 0
security_ct            0
late_aircraft_ct       0
arr_cancelled          0
arr_diverted           0
arr_delay              0
carrier_delay          0
weather_delay          0
nas_delay              0
security_delay         0
late_aircraft_delay    0
dtype: int64
```

📊 Exploratory Data Analysis

In this section, descriptive statistics and exploratory data analysis are conducted to understand the distribution, variability and relationships among key variables.

In [6]:
```
df.describe

df.columns

df['arr_delay'].describe()
```

Out[6]:
```
count       664.000000
mean      16968.751506
std       30465.088679
min           0.000000
25%        1642.000000
50%        6734.000000
75%       18158.000000
max      260257.000000
Name: arr_delay, dtype: float64
```

In [27]:
```
df['carrier']
```

Out[27]:
```
0      YX
1      G7
2      MQ
3      NK
4      UA
       ..
659    MQ
660    NK
661    OH
662    UA
663    YX
Name: carrier, Length: 664, dtype: object
```

In [20]:
```
average_delay = df['arr_delay'].mean()
average_delay
```

Out[20]:
```
16968.751506024095
```

In [23]:
```
cause_of_delay = df.groupby('carrier')[['carrier_delay', 'weather_delay', 'nas_delay', 'security_delay']].r
print(cause_of_delay)
```

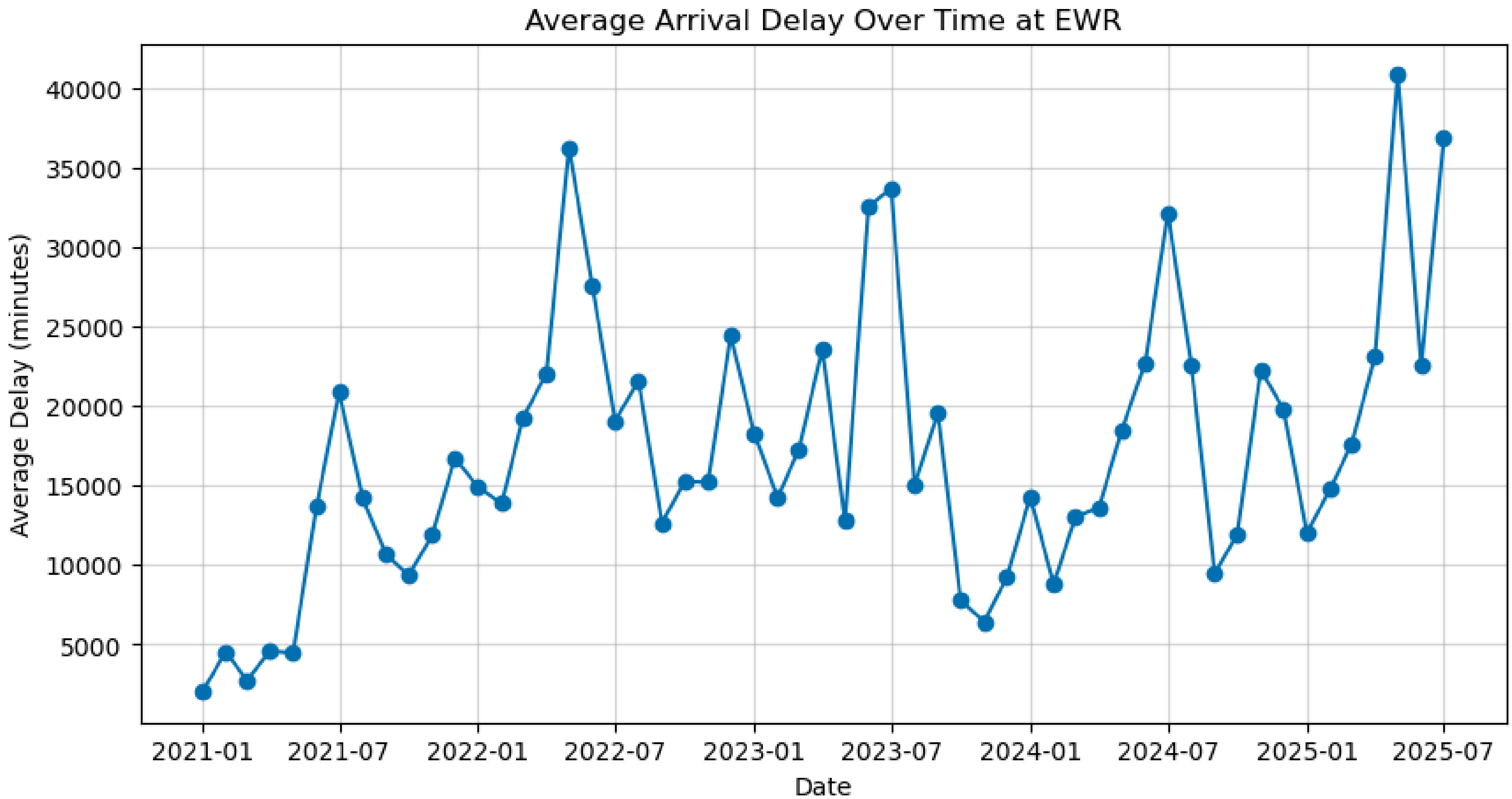
carrier	carrier_delay	weather_delay	nas_delay	security_delay
9E	475.600000	100.090909	961.800000	0.000000
AA	3526.709091	751.054545	3881.781818	49.836364
AS	817.309091	213.254545	2326.036364	7.836364
B6	5719.563636	465.509091	4478.309091	48.236364
C5	1165.900000	313.000000	912.400000	1.200000
DL	3062.963636	349.709091	3724.236364	4.836364
F9	1025.821429	94.500000	989.892857	0.000000
G4	229.600000	43.290909	187.709091	4.418182
G7	4122.472727	1644.054545	7995.727273	2.672727
MQ	141.589744	77.769231	329.589744	1.743590
NK	3019.545455	646.800000	7795.127273	88.200000
OH	17.666667	27.333333	61.666667	0.000000
OO	640.823529	181.852941	110.558824	4.382353
UA	23833.509091	5100.709091	35586.690909	7.600000
YX	5030.454545	1583.963636	13418.527273	11.545455

In this section, average flight delays are analyzed over time to identify monthly and yearly trends that may indicate seasonal effects or operational changes.

In [7]:

```
# Group by year and month
trend = df.groupby(['year', 'month'])['arr_delay'].mean().reset_index()
trend['date'] = pd.to_datetime(trend['year'].astype(str) + '-' + trend['month'].astype(str))

plt.figure(figsize=(10,5))
plt.plot(trend['date'], trend['arr_delay'], marker='o', color='#0072B2')
plt.title("Average Arrival Delay Over Time at EWR")
plt.xlabel("Date")
plt.ylabel("Average Delay (minutes)")
plt.grid(alpha=0.5)
plt.show()
```



🛬 Average Arrival Delay Trend at EWR (2021–2025)

Insights:

- Delays show **seasonal peaks**, especially between **July and August**, indicating high travel demand and congestion in summer.
- There are noticeable **spikes in mid-2022 and mid-2025**, suggesting significant disruption periods (possibly weather, staffing, or operational bottlenecks).
- Overall delay levels **increase gradually over the years**, indicating a growing strain on airport/airspace capacity.

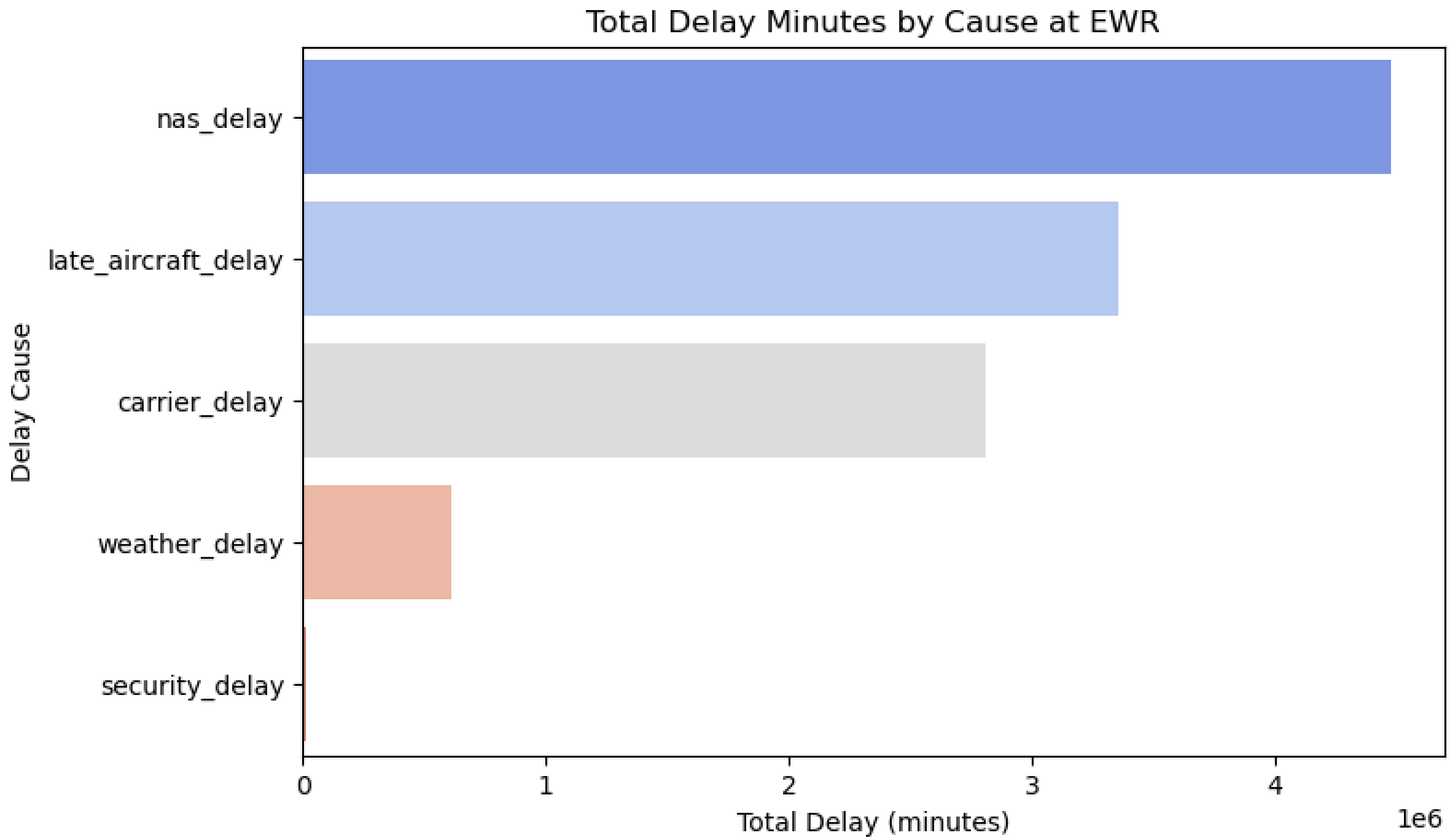
⚙️ Delay Causes Breakdown

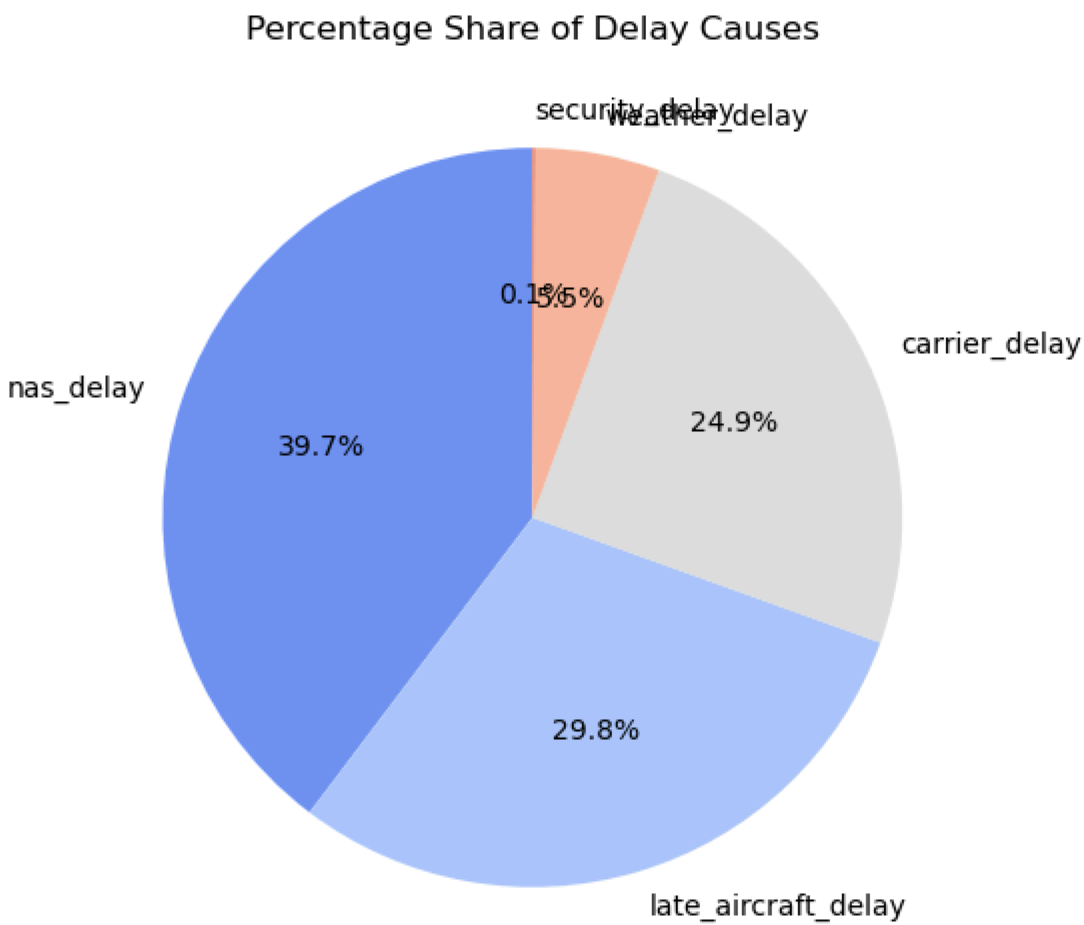
In this section, total delay minutes are aggregated by cause to determine which operational factors contribute most to overall delays.
This helps identify where efficiency improvements would have the strongest impact.

In [8]:
```
delay_causes = df[['carrier_delay','weather_delay','nas_delay','late_aircraft_delay','security_delay']].sur

plt.figure(figsize=(8,5))
sns.barplot(x=delay_causes.values, y=delay_causes.index, palette='coolwarm')
plt.title("Total Delay Minutes by Cause at EWR")
plt.xlabel("Total Delay (minutes)")
plt.ylabel("Delay Cause")
plt.show()

plt.figure(figsize=(6,6))
plt.pie(delay_causes.values, labels=delay_causes.index, autopct='%1.1f%%', startangle=90, colors=sns.color_
plt.title("Percentage Share of Delay Causes")
plt.show()
```


Total Delay Minutes by Cause at EWR
nas_delay
late_aircraft_delay
carrier_delay
weather_delay
security_delay
Delay Cause
0
1
2
3
4
1e6
Total Delay (minutes)



Total Delay Minutes by Cause at EWR

Insight:
Late aircraft and NAS delays contribute the **largest share** of total delay minutes, indicating **network congestion and turnaround inefficiencies** as dominant operational issues.

🔥 Full Variable Correlation Heatmap

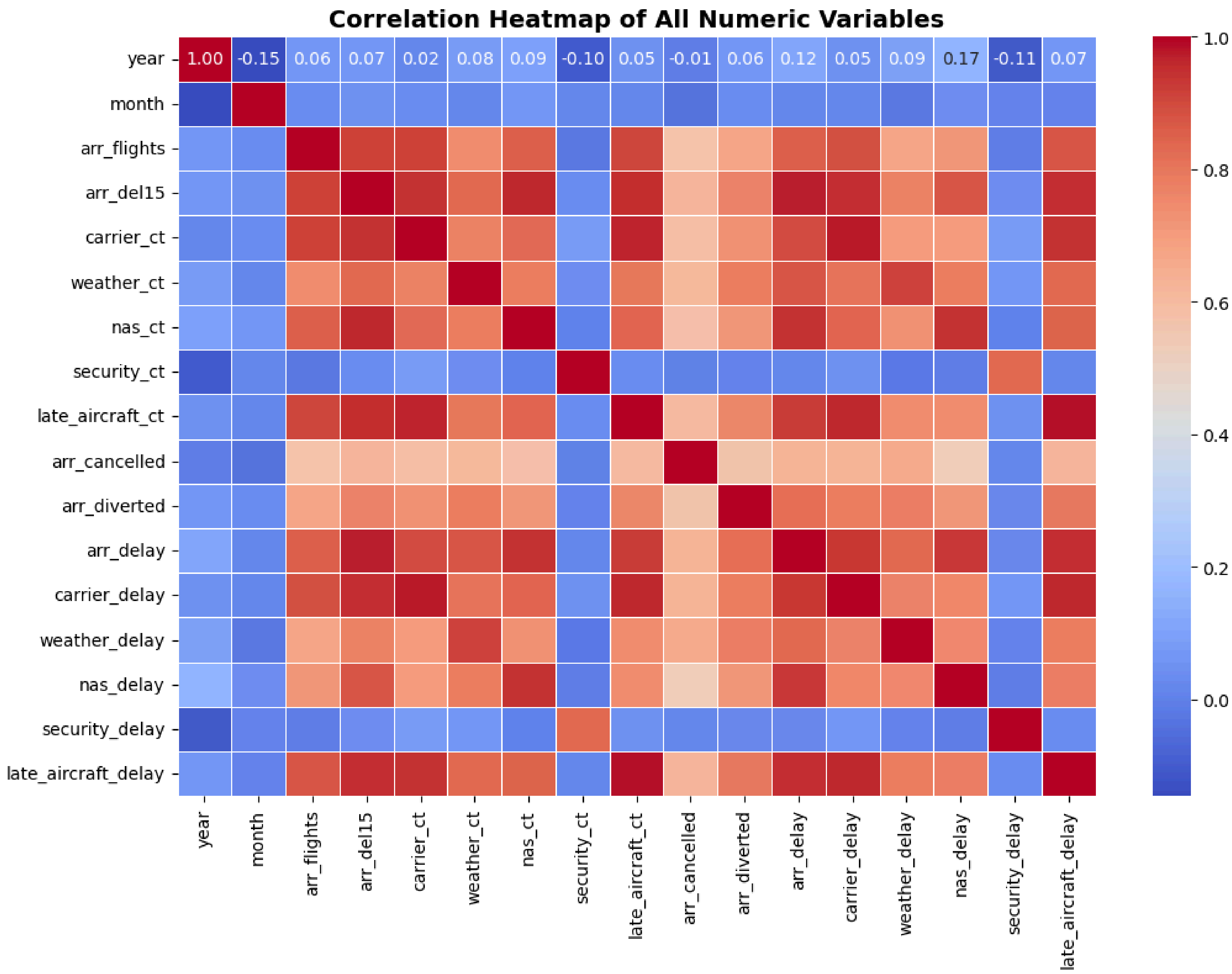
In this section a correlation heatmap is generated to compare how all numeric variables in the dataset relate to each other. This helps identify which factors move together and which have minimal relationship.

Higher positive correlation indicates that variables increase together, while negative correlation suggests an inverse relationship.

In [9]:
```
# Select only numeric columns
numeric_df = df.select_dtypes(include=['number'])

# Compute correlation
corr_matrix = numeric_df.corr()

# Plot heatmap
plt.figure(figsize=(12,8))
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm", linewidths=0.5, fmt=".2f")
plt.title("Correlation Heatmap of All Numeric Variables", fontsize=14, weight='bold')
plt.show()
```



Correlation Heatmap of All Numeric Variables

Insights:

The heatmap shows that NAS delays and Late Aircraft delays are strongly correlated, meaning delays in the air traffic system often lead to aircraft arriving late and causing further delays. Weather delays show low correlation, indicating they occur independently and are not the main driver of overall delays

🏁 Overall Insights Summary

Based on the visualizations and analysis, delays at Newark Liberty International Airport (EWR) are driven primarily by **operational and network-related factors**, not weather. The correlation and cause breakdown show that **Late Aircraft** and **NAS (Air Traffic / Congestion)** delays are the largest contributors to total delay minutes. This indicates that when flights arrive late the delay often cascades into subsequent flights.

Seasonal analysis shows **higher delays during summer months**, aligning with peak travel demand and congested airspace conditions. Airline comparisons reveal that some carriers consistently experience higher delay totals, suggesting differences in **scheduling efficiency, turnaround time, and resource planning**.

Overall, improving **aircraft turnaround processes**, **gate scheduling** and **traffic flow coordination** has a greater potential impact on reducing delays than weather-related interventions.