Exploratory Data Analysis (EDA) on MPG Dataset

Objective of the Analysis

The primary objective of this analysis is interpretation and insight generation, not prediction.

- Business / Analytical Value
- Understand drivers of fuel efficiency (MPG)
- Identify engineering trade-offs (weight, power, cylinders)
- Compare vehicle origin and era-based efficiency trends

Dataset Description & Summary

Dataset Source:

UCI Machine Learning Repository – Auto MPG Dataset

Description

The dataset contains technical specifications of cars manufactured between 1970–1982, along with their fuel efficiency.

Variable	Description
mpg	Miles per gallon (target variable)
cylinders	Number of engine cylinders
displacement	Engine displacement (cu. inches)
horsepower	Engine horsepower
weight	Vehicle weight (lbs)
acceleration	0–60 mph time (seconds)
model_year	Year of manufacture
origin	1=USA, 2=Europe, 3=Japan
name	Car model name

In [24]:
```
# Import Libraries & Load Data
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```python
sns.set(style="whitegrid", context="notebook")

# Load the dataset from seaborn
df = sns.load_dataset('mpg')

# Basic inspection
print("--- Data Info ---")
print(df.info())
print("\n--- Descriptive Statistics ---")
print(df.describe())
print("\n--- Missing Values ---")
print(df.isnull().sum())
```

```
--- Data Info ---
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   mpg           398 non-null    float64
 1   cylinders     398 non-null    int64
 2   displacement  398 non-null    float64
 3   horsepower    392 non-null    float64
 4   weight        398 non-null    int64
 5   acceleration  398 non-null    float64
 6   model_year    398 non-null    int64
 7   origin        398 non-null    object
 8   name          398 non-null    object
dtypes: float64(4), int64(3), object(2)
memory usage: 28.1+ KB
None

--- Descriptive Statistics ---
              mpg   cylinders  displacement  horsepower       weight  \
count  398.000000  398.000000    398.000000  392.000000   398.000000
mean    23.514573    5.454774    193.425879  104.469388  2970.424623
std      7.815984    1.701004    104.269838   38.491160   846.841774
min      9.000000    3.000000     68.000000   46.000000  1613.000000
25%     17.500000    4.000000    104.250000   75.000000  2223.750000
50%     23.000000    4.000000    148.500000   93.500000  2803.500000
75%     29.000000    8.000000    262.000000  126.000000  3608.000000
max     46.600000    8.000000    455.000000  230.000000  5140.000000

       acceleration  model_year
count    398.000000  398.000000
mean      15.568090   76.010050
std        2.757689    3.697627
min        8.000000   70.000000
25%       13.825000   73.000000
50%       15.500000   76.000000
75%       17.175000   79.000000
max       24.800000   82.000000

--- Missing Values ---
mpg             0
cylinders       0
displacement    0
horsepower      6
weight          0
acceleration    0
model_year      0
origin          0
name            0
dtype: int64
```

In [25]:

```python
# Dataset Size & Structure
df.shape

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   mpg           398 non-null    float64
 1   cylinders     398 non-null    int64
 2   displacement  398 non-null    float64
 3   horsepower    392 non-null    float64
 4   weight        398 non-null    int64
 5   acceleration  398 non-null    float64
 6   model_year    398 non-null    int64
 7   origin        398 non-null    object
 8   name          398 non-null    object
dtypes: float64(4), int64(3), object(2)
memory usage: 28.1+ KB
```

Initial Observations from mpg dataset

Dataset size: 398 rows × 9 columns

horsepower contains missing values

origin is categorical but encoded numerically

Data Exploration Plan

Planned EDA Workflow

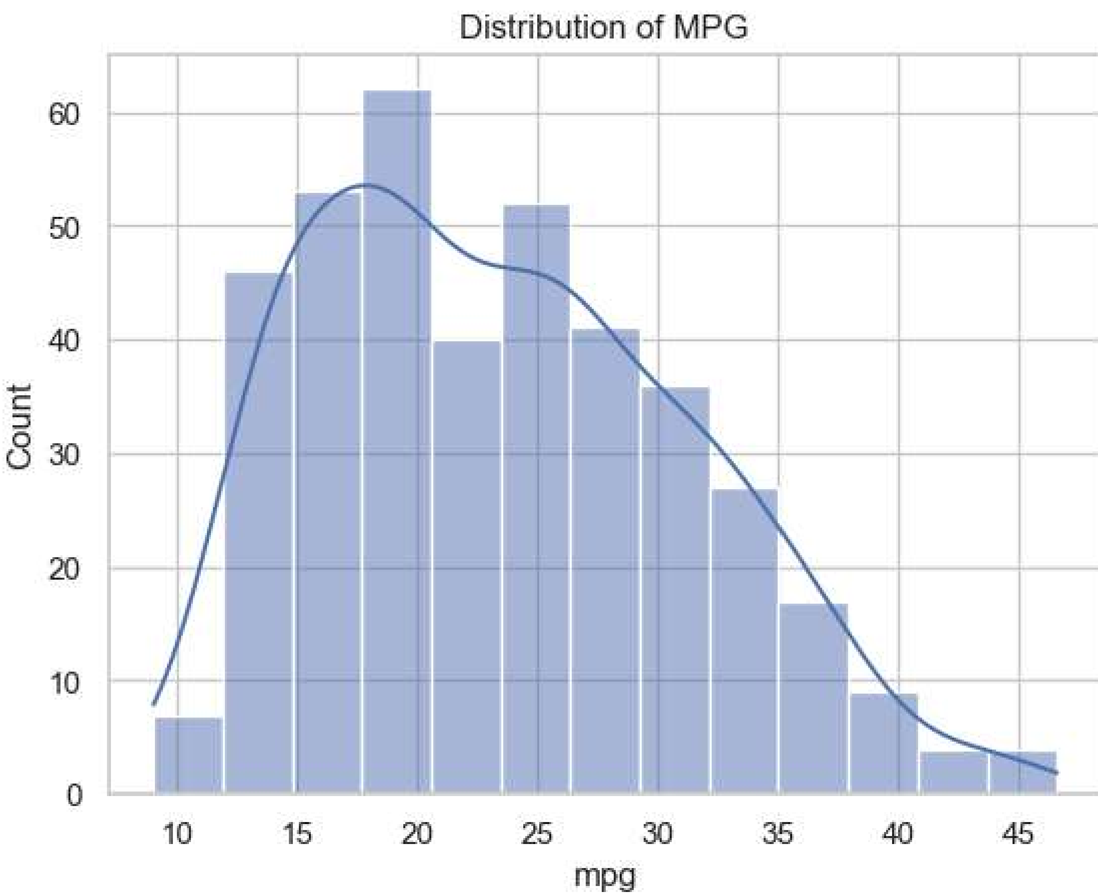
- Univariate analysis – distribution of MPG and features
- Bivariate analysis – relationship with MPG
- Multivariate patterns – interaction effects
- Data cleaning – missing values & data types
- Feature engineering – categorical encoding
- Hypothesis testing
- insights & next steps

In [26]:
```
# Data Cleaning
# Handling Missing Values
df.isnull().sum()

# Horsepower has missing values - impute using median
df['horsepower'] = df['horsepower'].fillna(df['horsepower'].median())

#Data Type Corrections
#df['origin'] = df['origin'].map({1: 'usa', 2: 'europe', 3: 'japan'})
```

In [27]:
```
# Feature Engineering
# Encoding Categorical Variables
#df_encoded = pd.get_dummies(df, columns=['origin'], drop_first=True)
#df_encoded.head()
```

```
# Year Binning (Era-Based Feature)
df['era'] = pd.cut(
    df['model_year'],
    bins=[69, 73, 77, 82],
    labels=['Early 70s', 'Mid 70s', 'Late 70s–Early 80s']
)
```

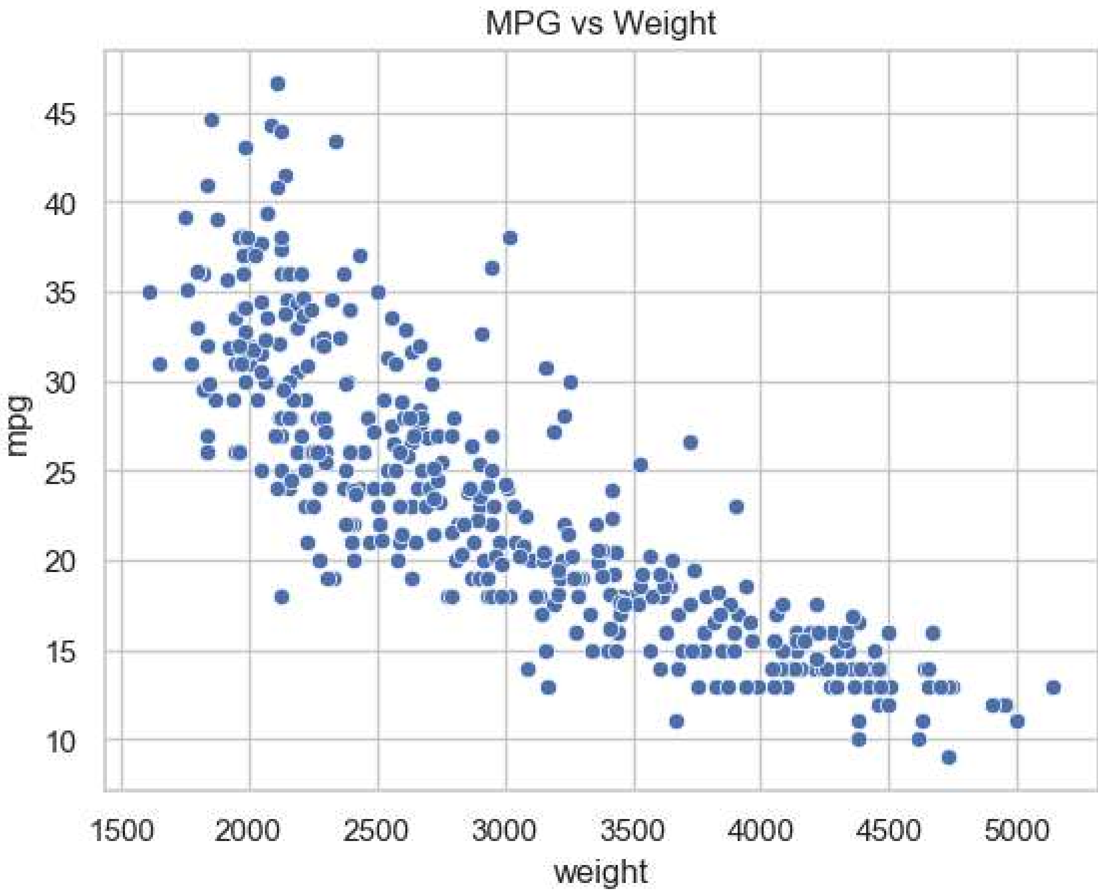
In [28]:
```
# Exploratory Data Analysis (EDA)
# Target Variable Distribution (MPG)
plt.figure()
sns.histplot(df['mpg'], kde=True)
plt.title("Distribution of MPG")
plt.show()
```



Insight

- MPG is right-skewed
- Majority vehicles fall between 15–30 MPG

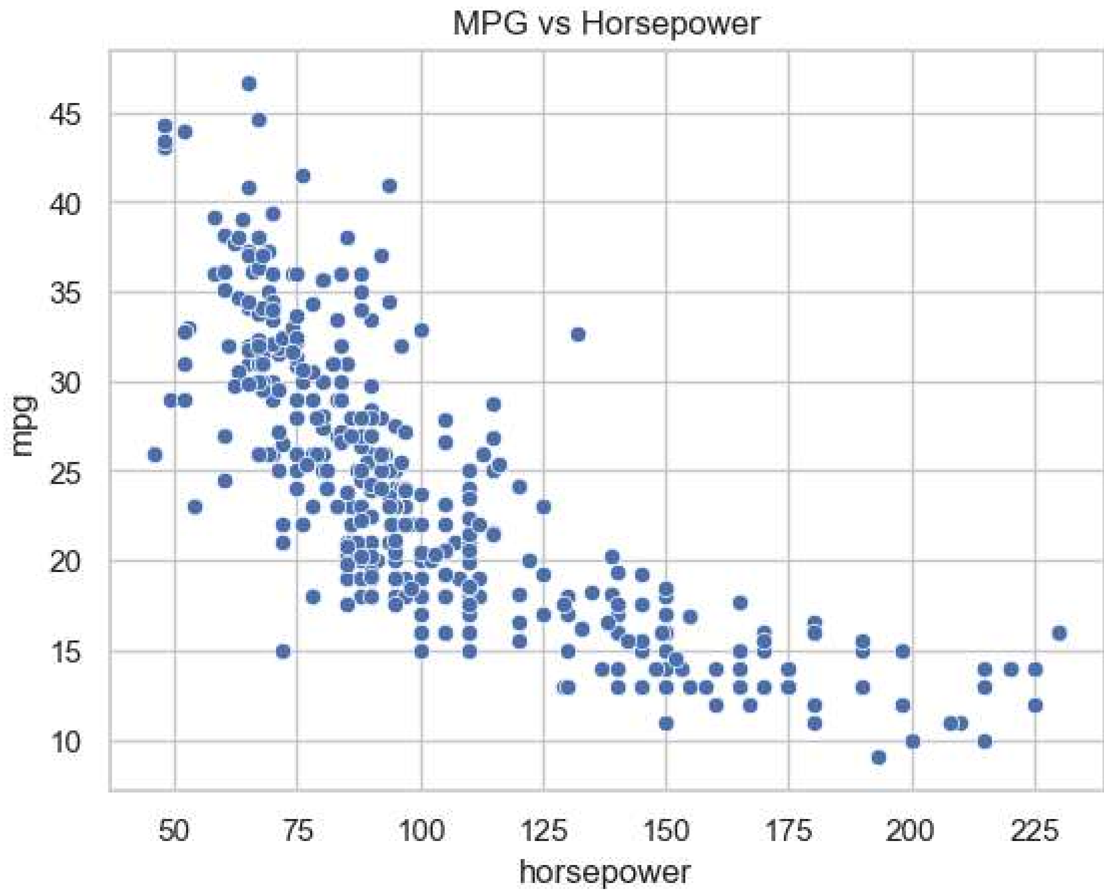
In [29]:
```
# MPG vs Weight
plt.figure()
sns.scatterplot(x='weight', y='mpg', data=df)
plt.title("MPG vs Weight")
plt.show()
```



Insight

- Strong negative relationship
- Heavier vehicles are consistently less fuel-efficient

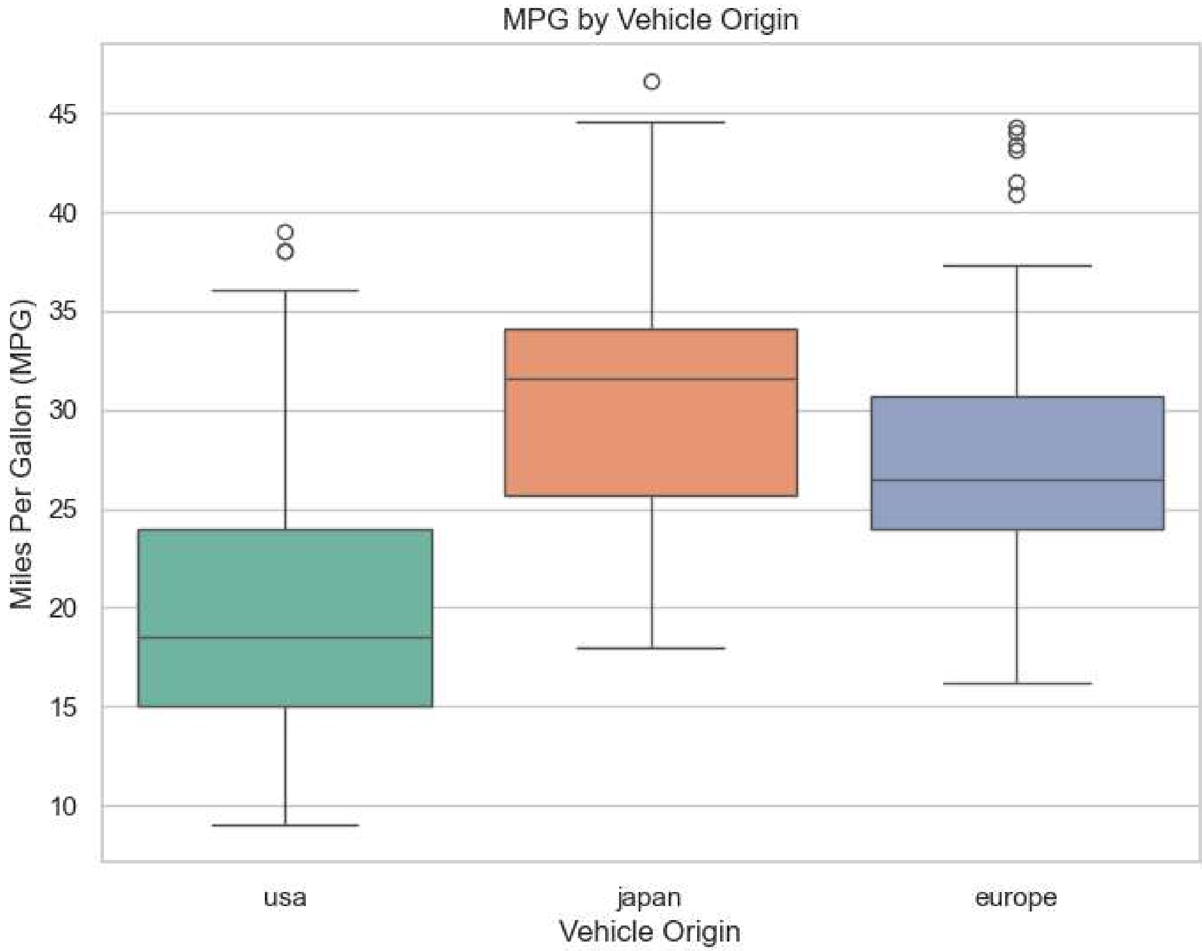
In [30]:
```
# MPG vs Horsepower
plt.figure()
sns.scatterplot(x='horsepower', y='mpg', data=df)
plt.title("MPG vs Horsepower")
plt.show()
```



Insight

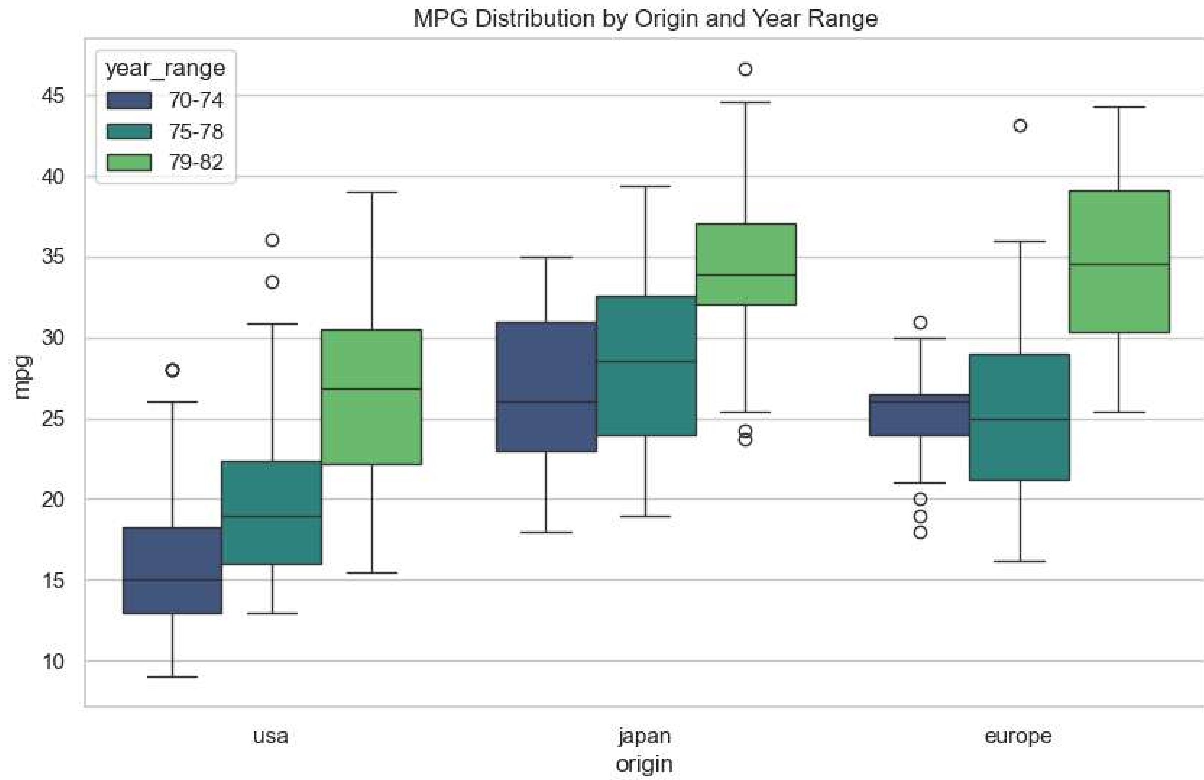
- Non-linear negative trend
- Performance-oriented vehicles sacrifice fuel efficiency

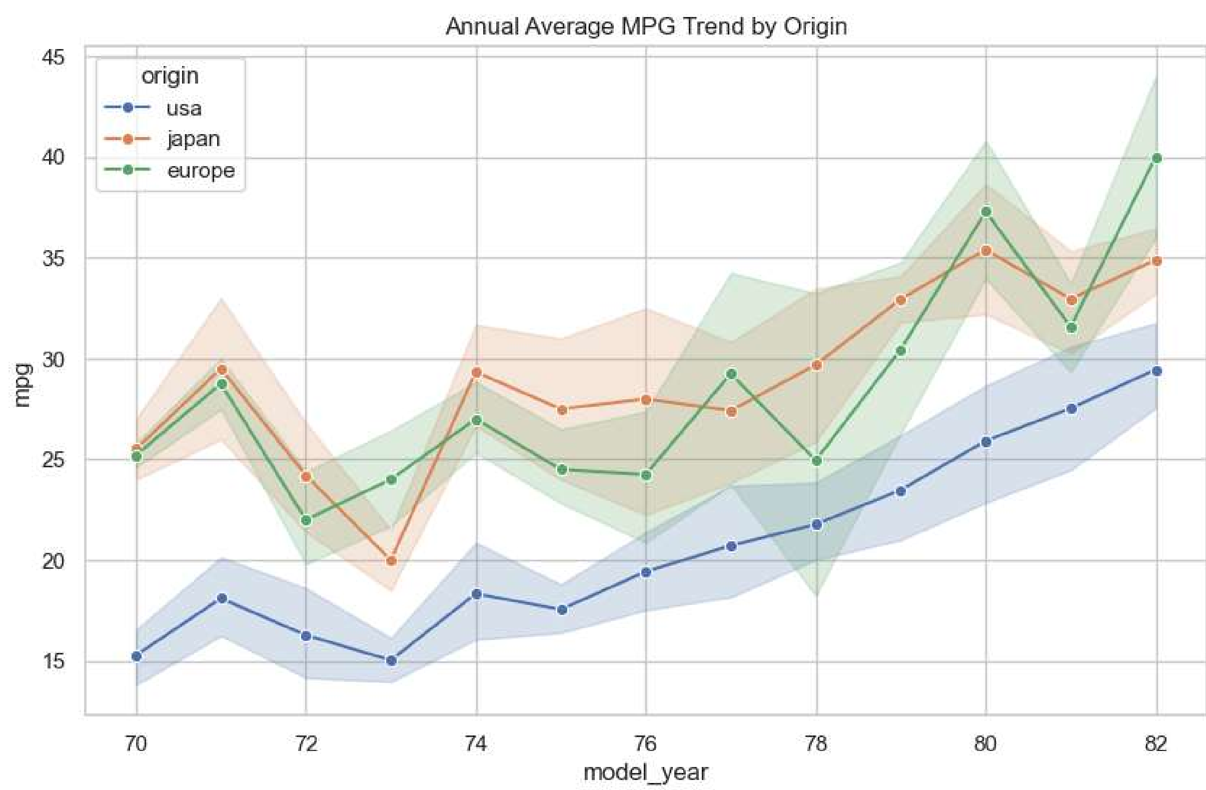
In [31]:
```
# MPG by Origin
# Initialize the figure
plt.figure(figsize=(8, 6))

# Create the boxplot
sns.boxplot(x='origin', y='mpg', data=df, palette='Set2', hue='origin', legend=Fals

plt.title("MPG by Vehicle Origin")
plt.xlabel("Vehicle Origin")
plt.ylabel("Miles Per Gallon (MPG)")

plt.show()
```



In [32]:

```
# Create a binned year column for a cleaner boxplot
df['year_range'] = pd.cut(df['model_year'], bins=[69, 74, 78, 83], labels=['70-74',

# Create the Boxplot
plt.figure(figsize=(10, 6))
sns.boxplot(x='origin', y='mpg', hue='year_range', data=df, palette='viridis')
plt.title('MPG Distribution by Origin and Year Range')
plt.show()

# Create a Line Plot for the annual trend
plt.figure(figsize=(10, 6))
sns.lineplot(x='model_year', y='mpg', hue='origin', marker='o', data=df)
plt.title('Annual Average MPG Trend by Origin')
plt.grid(True)
plt.show()
```



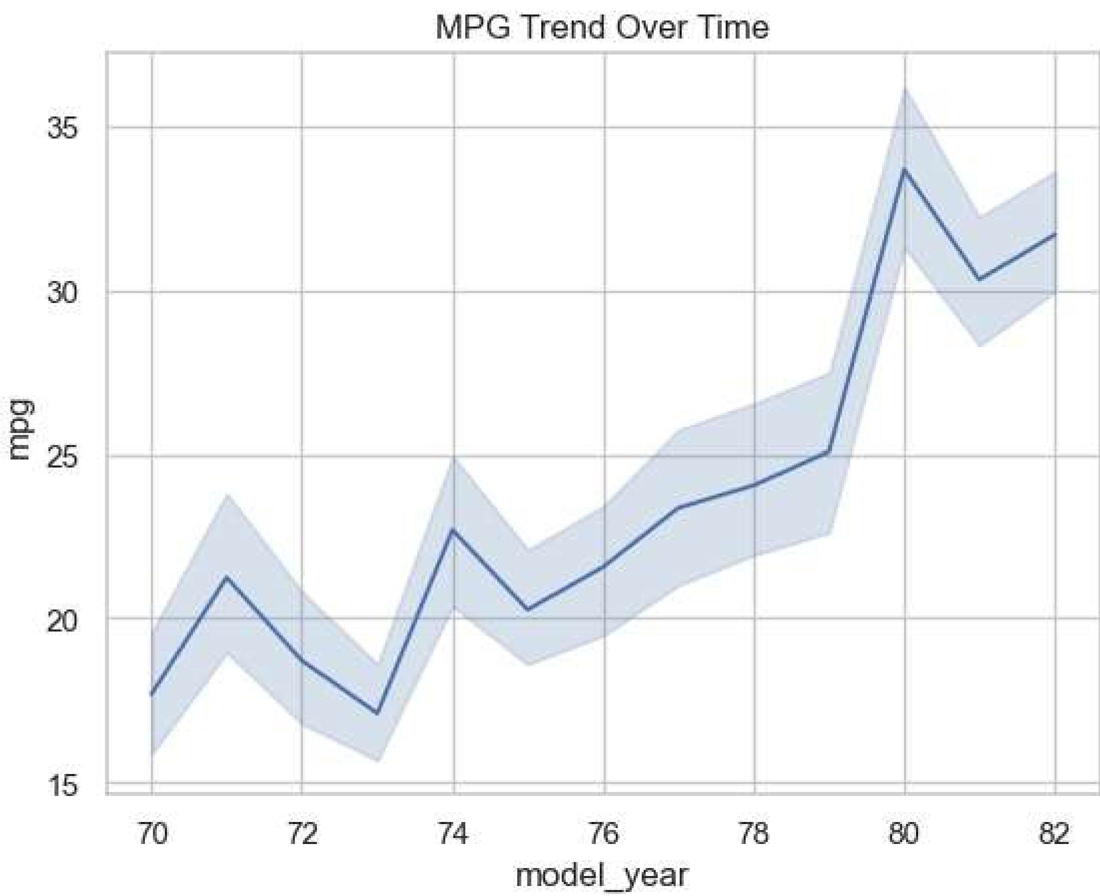


Insight

- Japanese and European cars are significantly more fuel-efficient than US cars

In [33]:
```
# MPG Trend Over Time
plt.figure()
sns.lineplot(x='model_year', y='mpg', data=df)
```

```
plt.title("MPG Trend Over Time")
plt.show()
```



Insight

- Clear improvement in MPG post mid-1970s
- Likely impact of oil crisis and regulations

Hypothesis Formulation

Hypothesis 1

Heavier cars have significantly lower MPG

Hypothesis 2

Cars manufactured after 1975 have higher MPG

Hypothesis 3

Japanese cars have higher MPG than US cars

Hypothesis Testing (Statistical Significance)

Testing Hypothesis 3

H_0: Mean MPG of Japanese cars ≤ Mean MPG of US cars H_1: Mean MPG of Japanese cars > Mean MPG of US cars

In [34]:
```
# Perform Two-Sample t-test
from scipy.stats import ttest_ind

mpg_japan = df[df['origin'] == 'japan']['mpg']
mpg_usa = df[df['origin'] == 'usa']['mpg']

t_stat, p_value = ttest_ind(mpg_japan, mpg_usa, equal_var=False)

# Formatted output
print("Two-Sample Welch's t-test: MPG Comparison (Japan vs USA)")
print("-" * 55)
print(f"Mean MPG (Japan): {mpg_japan.mean():.2f}")
print(f"Mean MPG (USA)  : {mpg_usa.mean():.2f}")
print(f"T-statistic    : {t_stat:.3f}")
print(f"P-value        : {p_value:.4f}")
```

```
Two-Sample Welch's t-test: MPG Comparison (Japan vs USA)
-------------------------------------------------------
Mean MPG (Japan): 30.45
Mean MPG (USA)  : 20.08
T-statistic    : 13.019
P-value        : 0.0000
```

Interpretation

$p\text{-value} < 0.001$

Reject null hypothesis at 95% confidence

Conclusion

Japanese cars are statistically significantly more fuel-efficient than US cars.

This result is both statistically and practically meaningful, reinforcing engineering and policy-driven narratives.

Key Findings & Insights

- Weight is the strongest negative driver of MPG
- Horsepower and displacement reduce fuel efficiency
- Post-1975 vehicles show technological efficiency gains
- Japanese manufacturers lead in fuel efficiency
- US cars prioritize power over efficiency in this era

Conclusions & Next Steps

- Fuel efficiency is primarily governed by vehicle mass and engine design
- Regulations and market forces strongly influence technological shifts
- Origin-based design philosophies significantly impact MPG

Recommended Next Steps

- Build predictive regression / ML models