mini-project-2

April 20, 2025

[48]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Data Loading and Inspection: Understand the structure of the dataset. Identify the types of information available

[49]:
```
df = pd.read_csv("/Vehicle_Insurance.csv")

print("Dataset shape:", df.shape)
df.info()
df.head()
```

```
Dataset shape: (381109, 12)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 381109 entries, 0 to 381108
Data columns (total 12 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   id                    381109 non-null  int64
 1   Gender                381109 non-null  object
 2   Age                   381109 non-null  int64
 3   Driving_License       381109 non-null  int64
 4   Region_Code           381109 non-null  float64
 5   Previously_Insured    381109 non-null  int64
 6   Vehicle_Age           381109 non-null  object
 7   Vehicle_Damage        381109 non-null  object
 8   Annual_Premium        381109 non-null  float64
 9   Policy_Sales_Channel  381109 non-null  float64
 10  Vintage               381109 non-null  int64
 11  Response              381109 non-null  int64
dtypes: float64(3), int64(6), object(3)
memory usage: 34.9+ MB
```

[49]:

	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	\
0	1	Male	44	1	28.0	0	
1	2	Male	76	1	3.0	0	

```
2   3    Male   47               1         28.0                    0
3   4    Male   21               1         11.0                    1
4   5  Female   29               1         41.0                    1

  Vehicle_Age Vehicle_Damage  Annual_Premium  Policy_Sales_Channel  Vintage  \
0   > 2 Years            Yes         40454.0                  26.0      217
1    1-2 Year             No         33536.0                  26.0      183
2   > 2 Years            Yes         38294.0                  26.0       27
3    < 1 Year             No         28619.0                 152.0      203
4    < 1 Year             No         27496.0                 152.0       39

   Response
0         1
1         0
2         1
3         0
4         0
```

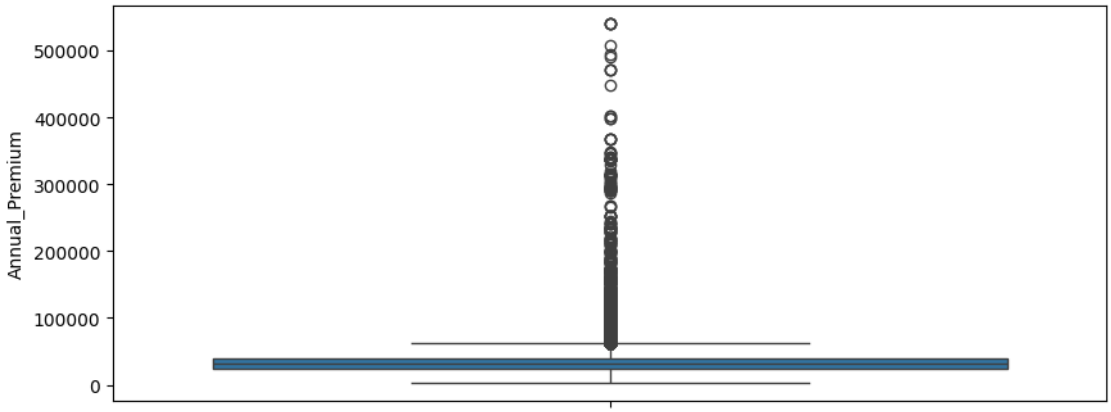
Data Cleaning: Handle missing values and outliers appropriately.

[50]:
```
# Check for missing values
df.isnull().sum()
```

[50]:
```
id                    0
Gender                0
Age                   0
Driving_License       0
Region_Code           0
Previously_Insured    0
Vehicle_Age           0
Vehicle_Damage        0
Annual_Premium        0
Policy_Sales_Channel  0
Vintage               0
Response              0
dtype: int64
```

[51]:
```
# Outlier detection
plt.figure(figsize=(10, 4))
sns.boxplot(df["Annual_Premium"])
```

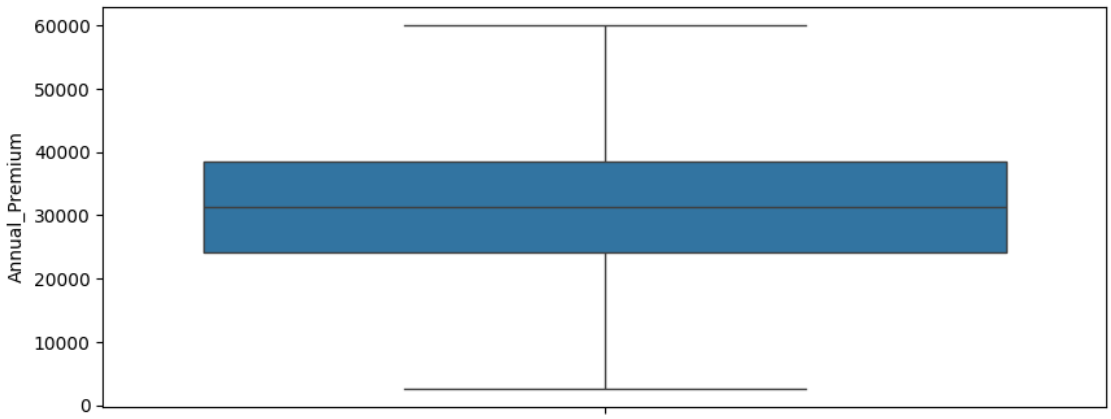
[51]:
```
<Axes: ylabel='Annual_Premium'>
```



[60]:
```
# Handling outliers using IQR
Q1 = df["Annual_Premium"].quantile(0.25)
Q3 = df["Annual_Premium"].quantile(0.75)
IQR = Q3 - Q1
lower = Q1 - 1.5 * IQR
upper = Q3 + 1.5 * IQR
df=df[(df["Annual_Premium"] >= lower) & (df["Annual_Premium"] <= upper)]
```

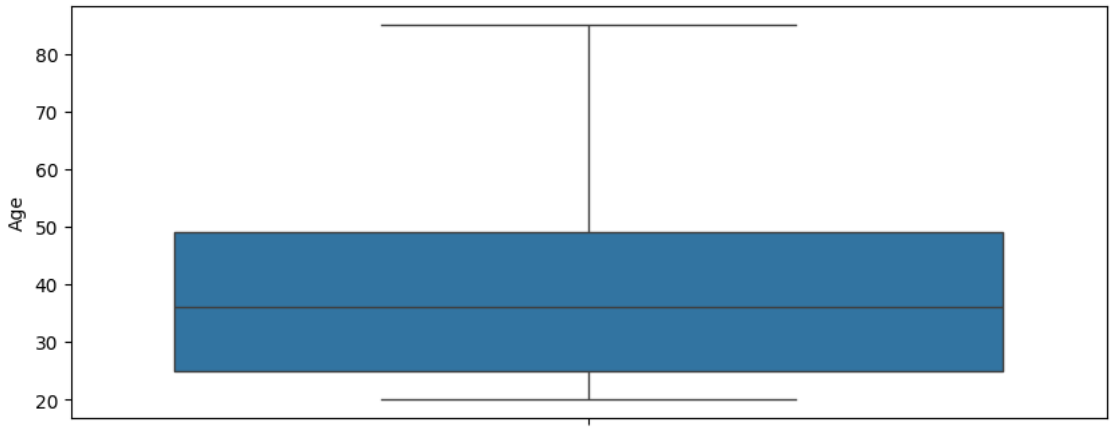
[61]:
```
plt.figure(figsize=(10, 4))
sns.boxplot(df["Annual_Premium"])
```

[61]: <Axes: ylabel='Annual_Premium'>



[62]:
```
plt.figure(figsize=(10, 4))
sns.boxplot(df["Age"])
```

[62]: <Axes: ylabel='Age'>



FUNCTION TO FIND OUTLIERS

[63]:
```
#finding all numeric columns
numeric_columns = df.select_dtypes(include=[np.number]).columns
numeric_columns
```

[63]:
```
Index(['id', 'Age', 'Driving_License', 'Region_Code', 'Previously_Insured',
       'Annual_Premium', 'Policy_Sales_Channel', 'Vintage', 'Response'],
      dtype='object')
```

[65]:
```
def finding_outliers(df, col):
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower = Q1 - 1.5 * IQR
    upper = Q3 + 1.5 * IQR
    outliers = df[(df[col] < lower) | (df[col] > upper)]  # Corrected line
    return outliers.shape[0] #to return the count of outliers
```

[ ]:
```
# Iterate over numeric columns
for col in numeric_columns:
    num_outliers = finding_outliers(df, col) #df is the dataframe
    print(f"Column {col}: {num_outliers} outliers")
```

```
Column id: 0 outliers
Column Age: 0 outliers
Column Driving_License: 763 outliers
Column Region_Code: 0 outliers
Column Previously_Insured: 0 outliers
Column Annual_Premium: 1510 outliers
Column Policy_Sales_Channel: 0 outliers
Column Vintage: 0 outliers
Column Response: 45155 outliers
```

[68]:
```
# Outlier detection
plt.figure(figsize=(10, 4))
sns.boxplot(df["Driving_License"])
```

[68]: <Axes: ylabel='Driving_License'>

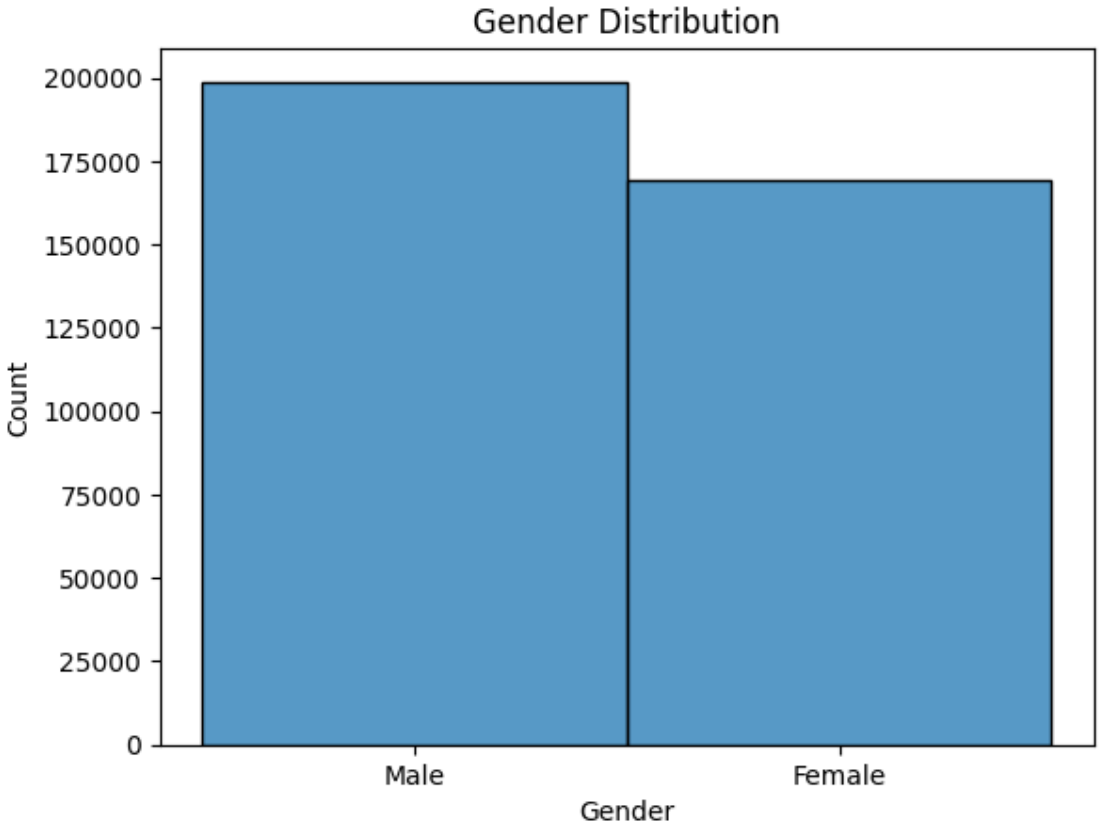
[67]:
```
# Handling outliers using IQR
Q1 = df["Driving_License"].quantile(0.25)
Q3 = df["Driving_License"].quantile(0.75)
IQR = Q3 - Q1
lower = Q1 - 1.5 * IQR
upper = Q3 + 1.5 * IQR
df=df[(df["Driving_License"] >= lower) & (df["Driving_License"] <= upper)]
```

[69]:
```
plt.figure(figsize=(10, 4))
sns.boxplot(df["Driving_License"])
```

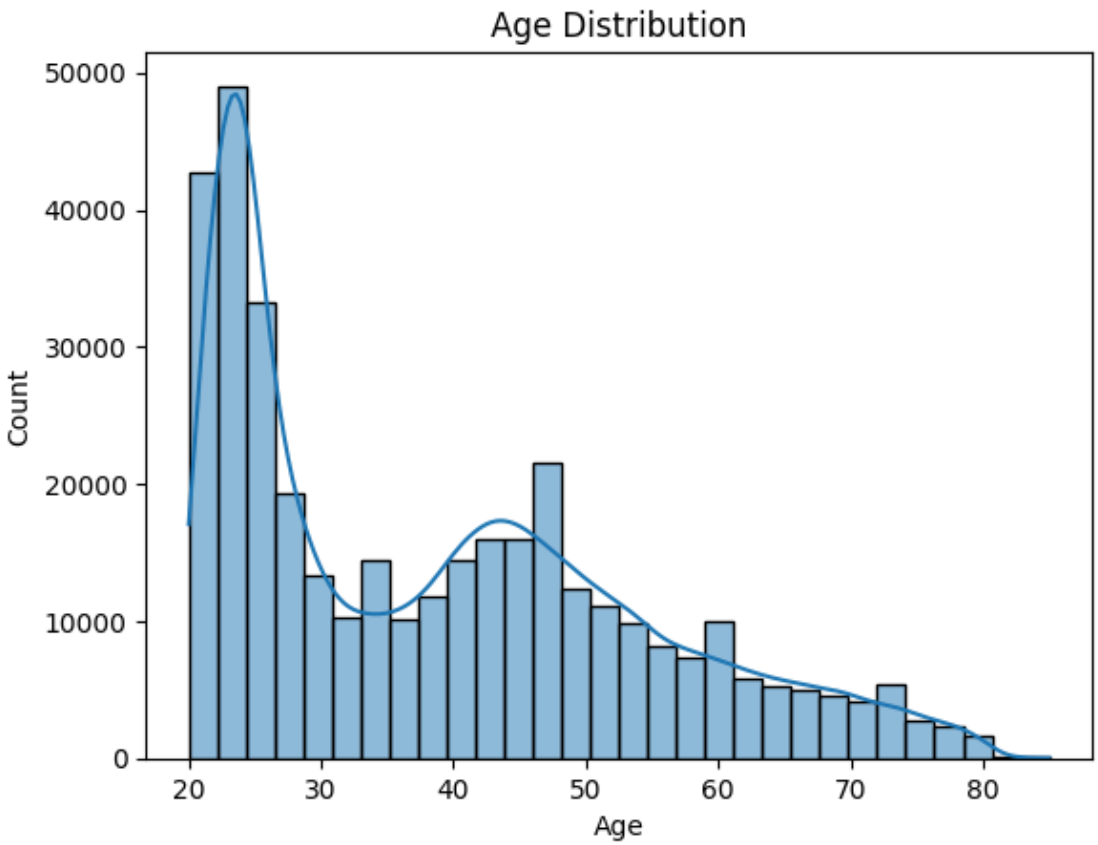
[69]: <Axes: ylabel='Driving_License'>

Data Visualization: Utilize various visualization techniques to explore the distribution of key variables.

[70]:
```
sns.histplot(data=df, x='Gender')
plt.title('Gender Distribution')
plt.show()
```

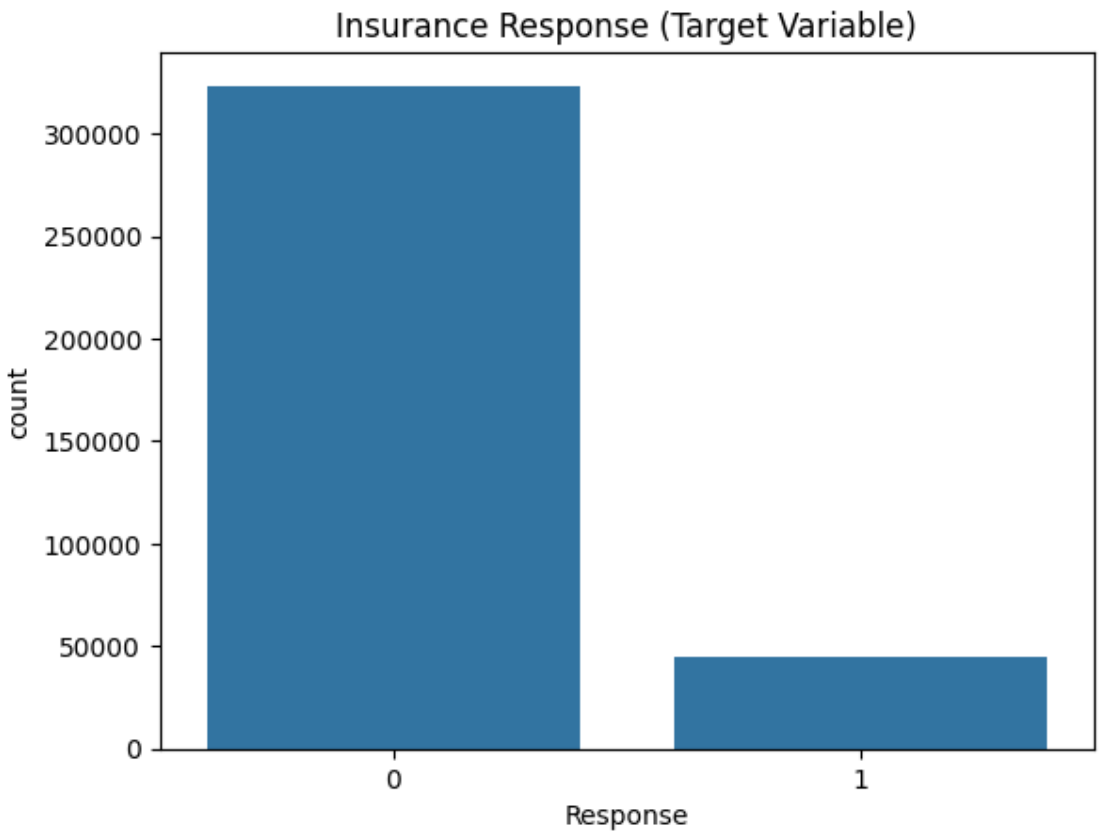


[71]:
```
sns.histplot(df['Age'], bins=30, kde=True)
plt.title('Age Distribution')
plt.show()
```

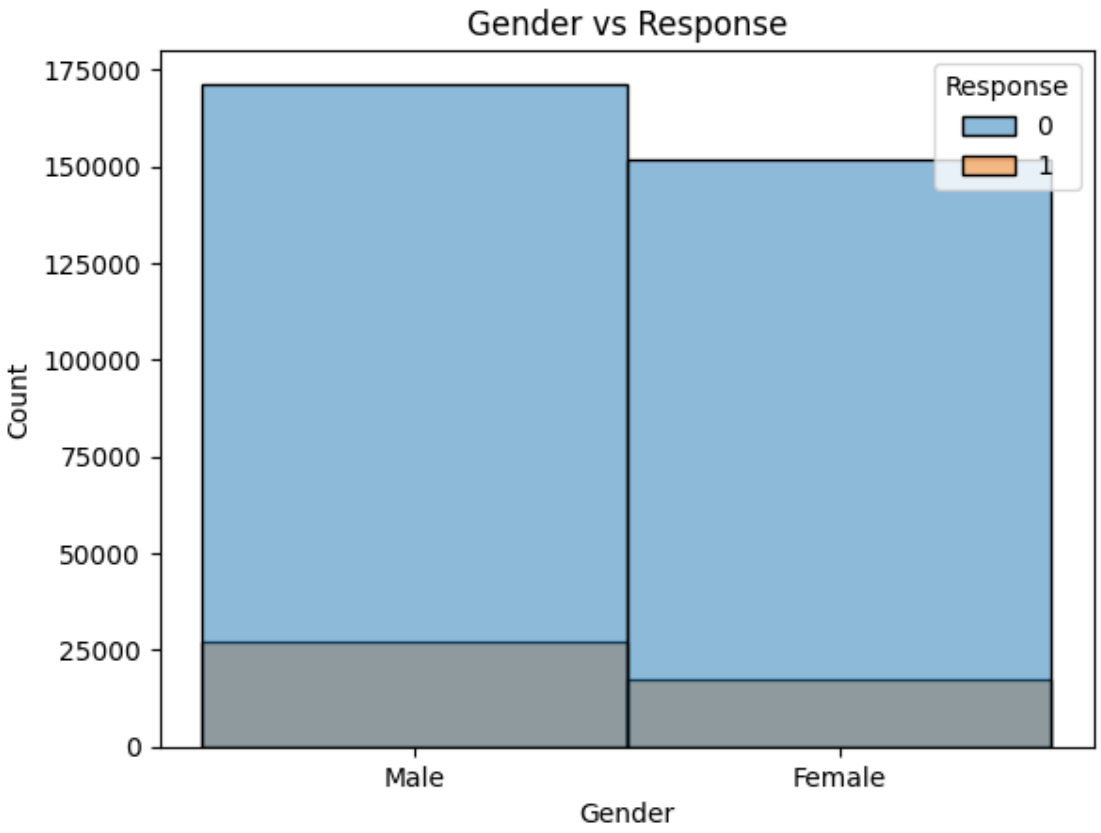


Feature Analysis: Examine the relationship between features and the target variable (insurance claims).

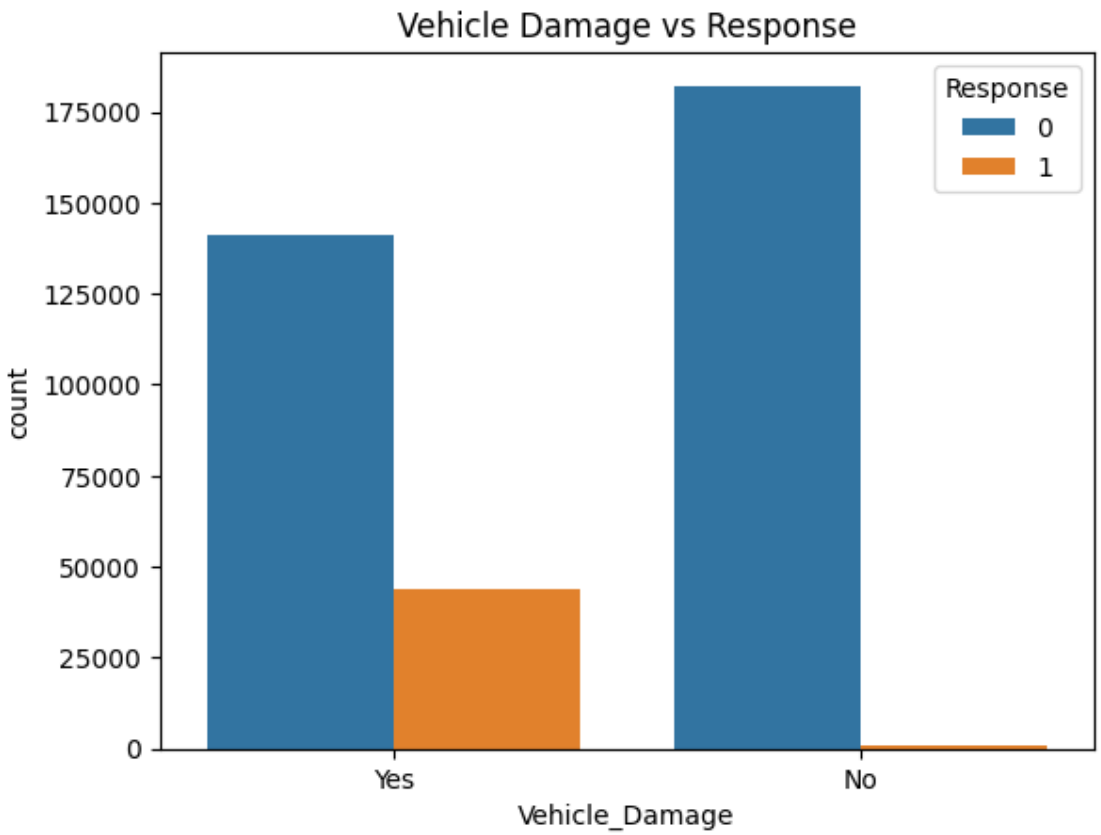
[72]:
```
# Response (target variable) distribution
sns.countplot(x='Response', data=df)
plt.title('Insurance Response (Target Variable)')
plt.show()
```



[73]:
```
# Gender vs Response
sns.histplot(x='Gender', hue='Response', data=df)
plt.title('Gender vs Response')
plt.show()
```

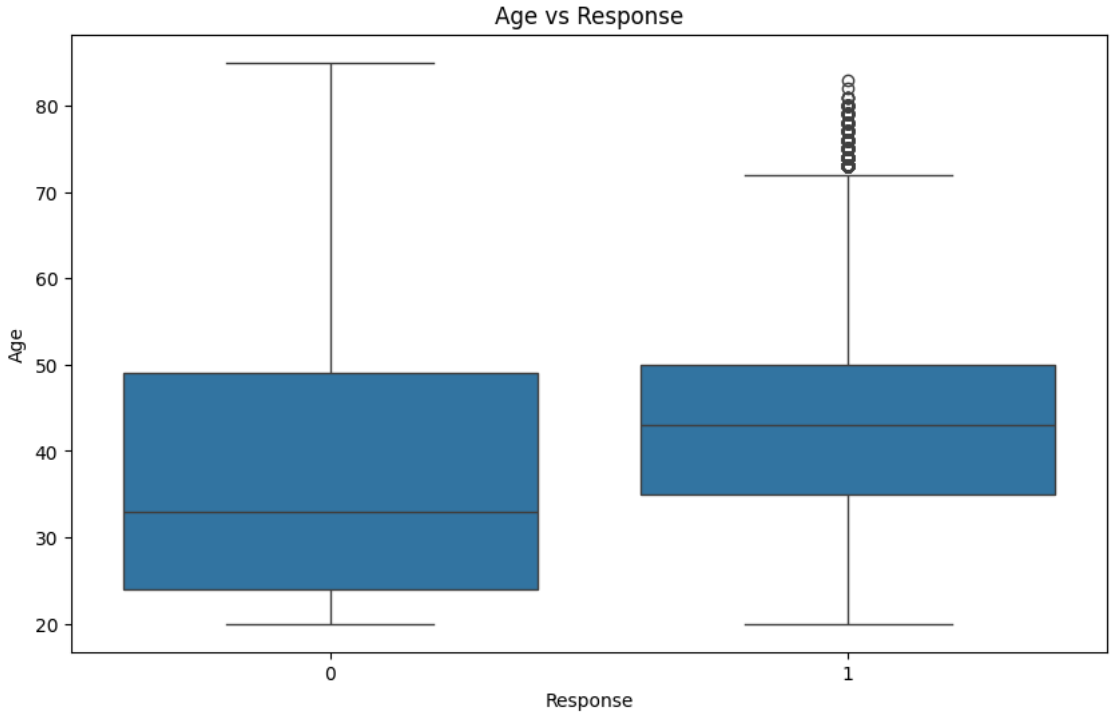


[74]:
```
# Vehicle_Damage vs Response
sns.countplot(x='Vehicle_Damage', hue='Response', data=df)
plt.title('Vehicle Damage vs Response')
plt.show()
```



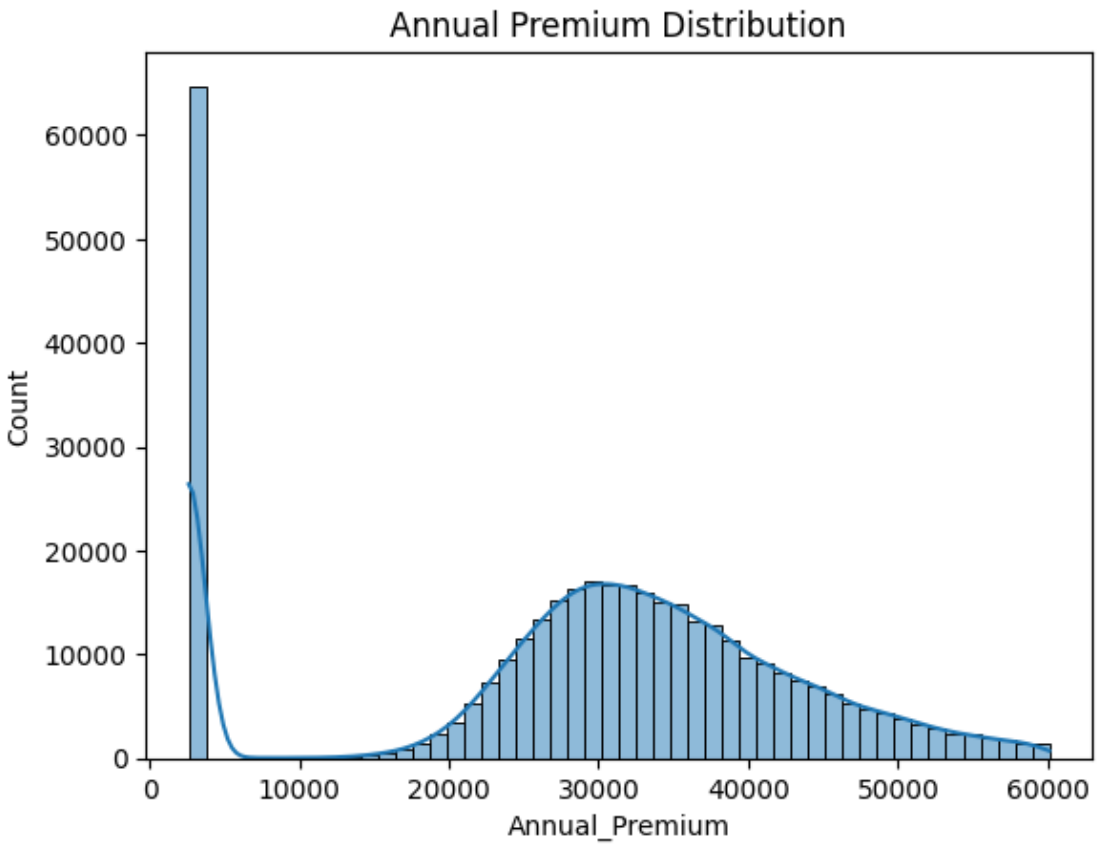
Age Distribution: Analyze the age distribution within the dataset and its impact on insurance claims.

[76]:
```
# Age vs Response
plt.figure(figsize=(10, 6))
sns.boxplot(x='Response', y='Age', data=df)
plt.title('Age vs Response')
plt.show()
```

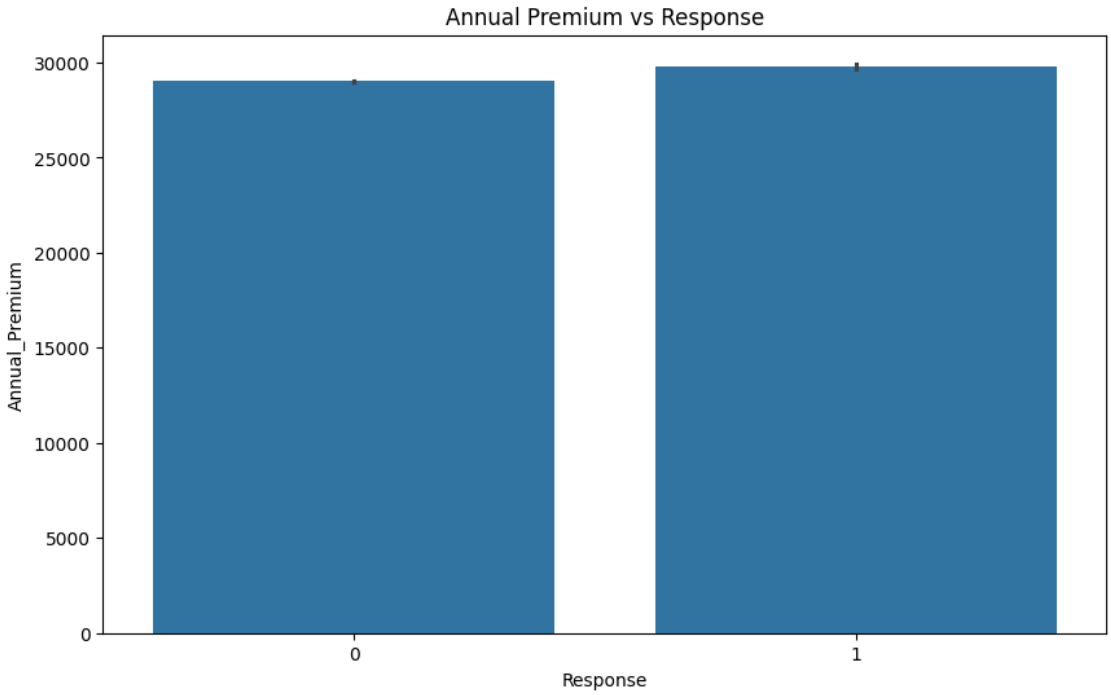


Premium Analysis: Investigate the distribution of insurance premiums and their correlation with claim frequencies.

[77]:
```
# Distribution of Premiums
sns.histplot(df['Annual_Premium'], bins=50, kde=True)
plt.title('Annual Premium Distribution')
plt.show()
```

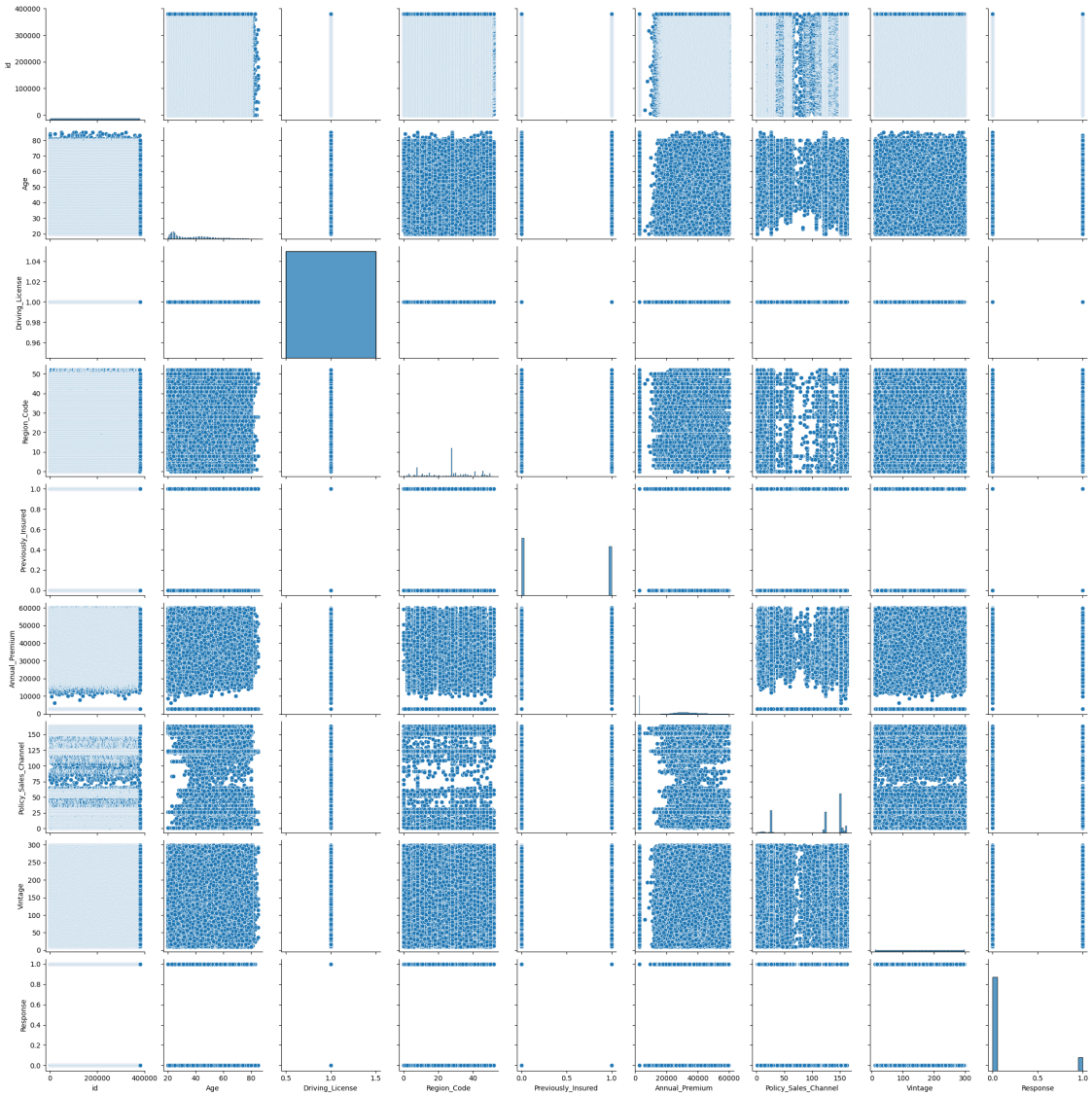


[78]:
```
# Premium vs Response
plt.figure(figsize=(10, 6))
sns.barplot(x='Response', y='Annual_Premium', data=df)
plt.title('Annual Premium vs Response')
plt.show()
```



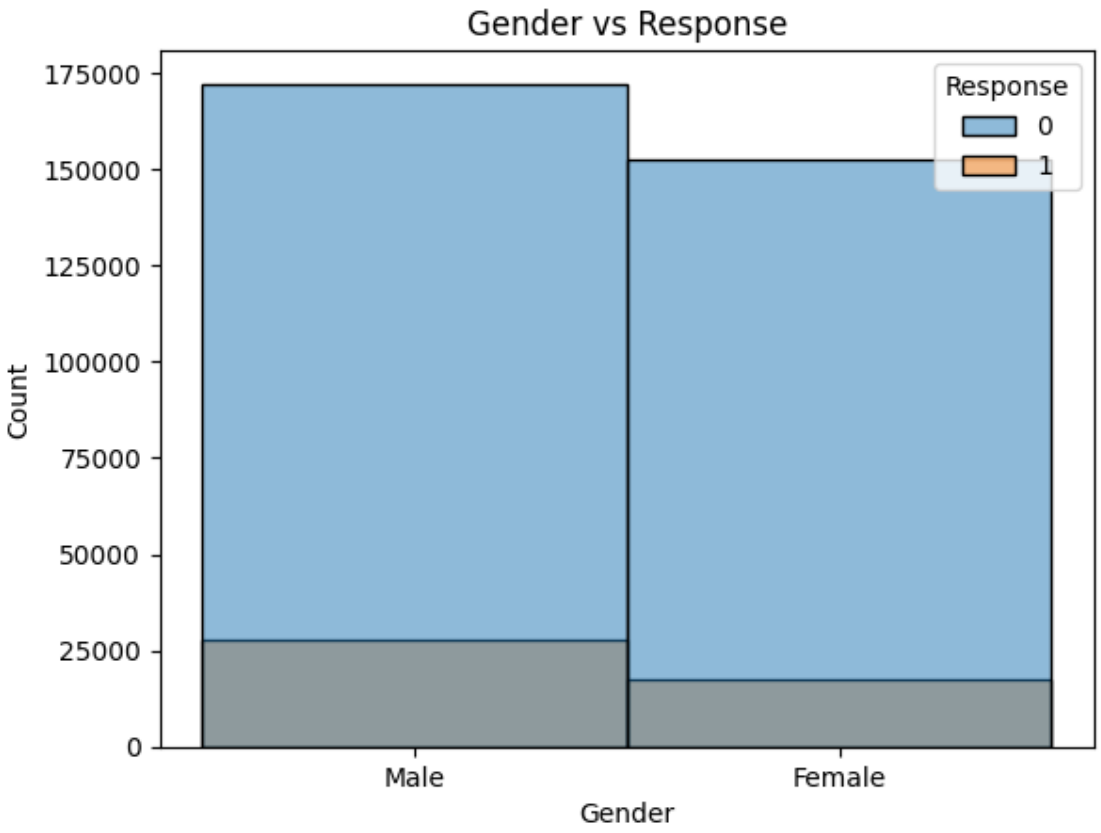
Claim Frequencies: Explore factors contributing to higher claim frequencies

[79]:
```
sns.pairplot(data=df)
plt.show()
```



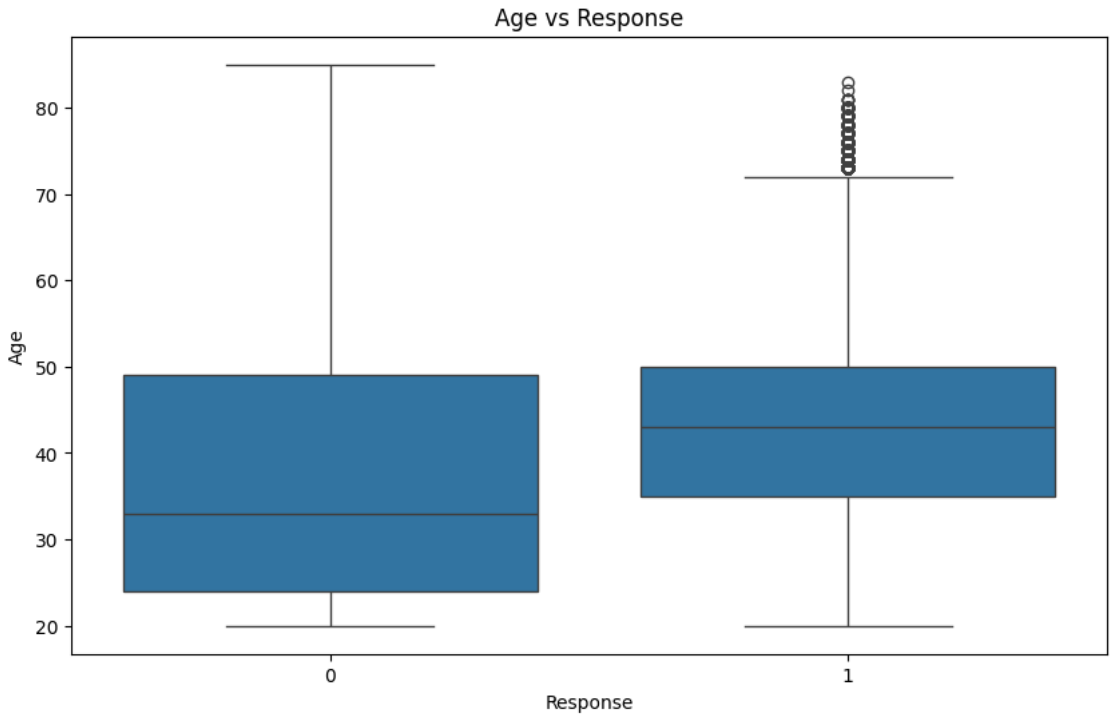
Gender Analysis: Investigate the role of gender in insurance claims.

[45]:
```
# Gender vs Response
sns.histplot(x='Gender', hue='Response', data=df)
plt.title('Gender vs Response')
plt.show()
```



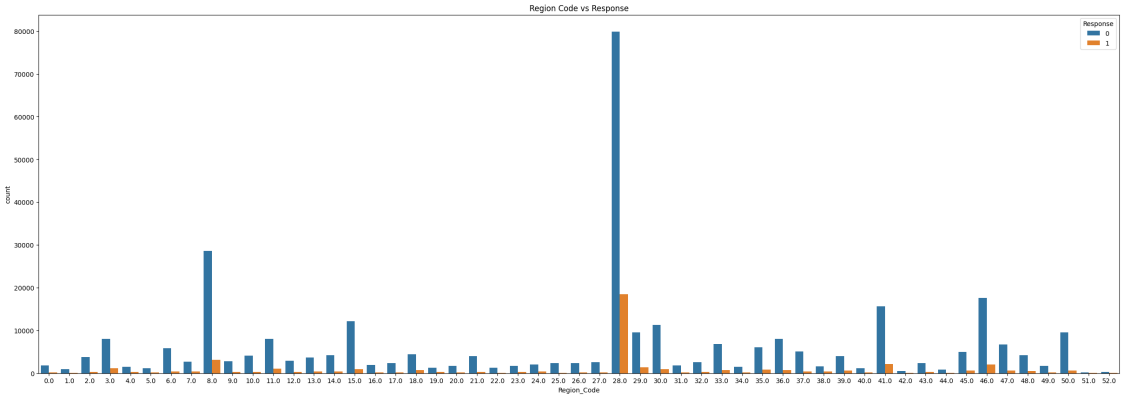
Vehicle Age and Claims: Examine the impact of vehicle age on the likelihood of a claim

[80]:
```
# Age vs Response
plt.figure(figsize=(10, 6))
sns.boxplot(x='Response', y='Age', data=df)
plt.title('Age vs Response')
plt.show()
```



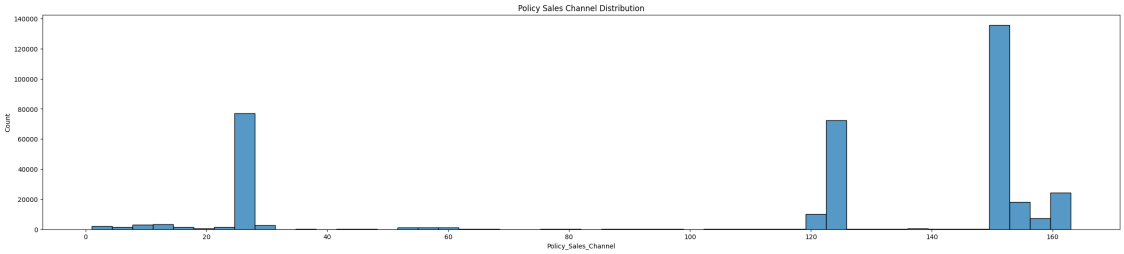
Region-wise Analysis: Analyze regional patterns in insurance claims.

[87]:
```
#Region vs Response
plt.figure(figsize=(30, 10))
sns.countplot(x='Region_Code', hue='Response', data=df)
plt.title('Region Code vs Response')
plt.show()
```

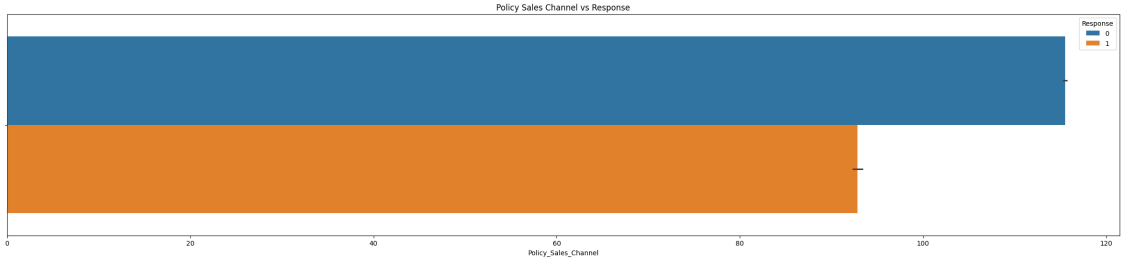


Policy Analysis: Explore the distribution and impact of different insurance policy types.

[91]:
```
#exploring distribution
plt.figure(figsize=(30, 6))
sns.histplot(x='Policy_Sales_Channel', data=df)
plt.title('Policy Sales Channel Distribution')
plt.show()
```

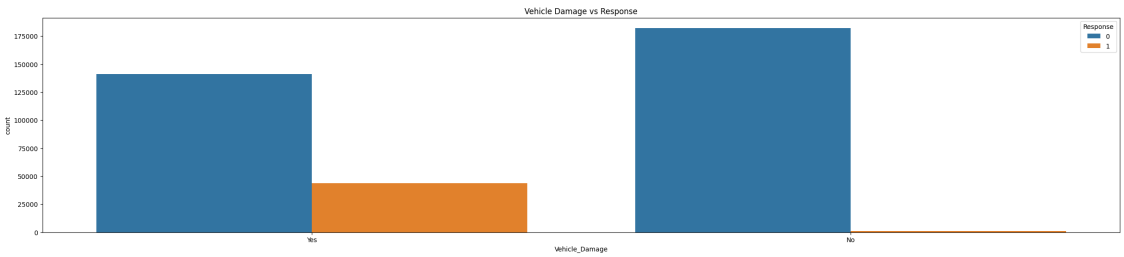


[93]:
```
#impact of different insurance policy types.
plt.figure(figsize=(30, 6))
sns.barplot(x='Policy_Sales_Channel', hue='Response', data=df)
plt.title('Policy Sales Channel vs Response')
plt.show()
```



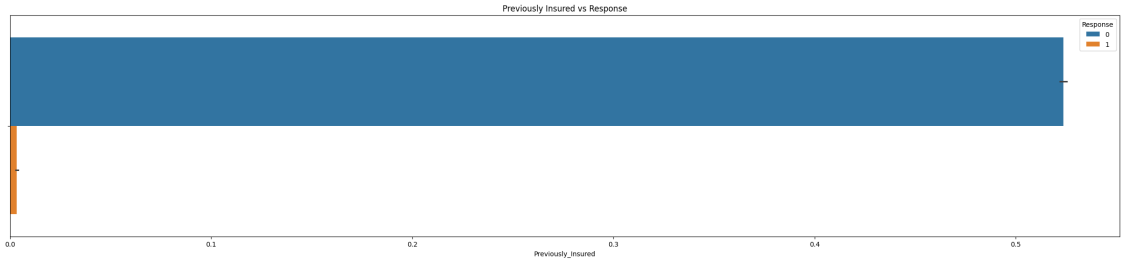
Claim Frequency by Vehicle Damage: Investigate the relationship between vehicle damage and claim frequencies.

[94]:
```
plt.figure(figsize=(30, 6))
sns.countplot(x='Vehicle_Damage', hue='Response', data=df)
plt.title('Vehicle Damage vs Response')
plt.show()
```



Customer Loyalty: Analyze if the number of policies held by a customer influences claim likelihood.

[95]:
```
plt.figure(figsize=(30, 6))
sns.barplot(x='Previously_Insured', hue='Response', data=df)
plt.title('Previously Insured vs Response')
plt.show()
```



[ ]: