Exploratory Data Analysis(EDA) on Vehicle Insurance

1.Importing Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

2.Loading Dataset

In [3]:
```
df=pd.read_csv("D:/SKCL/Python/Vehicle_Insurance.csv")
```

3.Understanding the structure of the dataset

In [5]:
```
df.head(10)
```

Out[5]:

	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	Vehicl
0	1	Male	44	1	28.0	0	> 2
1	2	Male	76	1	3.0	0	1-
2	3	Male	47	1	28.0	0	> 2
3	4	Male	21	1	11.0	1	<
4	5	Female	29	1	41.0	1	<
5	6	Female	24	1	33.0	0	<
6	7	Male	23	1	11.0	0	<
7	8	Female	56	1	28.0	0	1-
8	9	Female	24	1	3.0	1	<
9	10	Female	32	1	6.0	1	<

4.Identifying the types of information available

In [10]:
```
df.describe().T
```

Out[10]:

	count	mean	std	min	25%
id	381109.0	190555.000000	110016.836208	1.0	95278.0
Age	381109.0	38.822584	15.511611	20.0	25.0
Driving_License	381109.0	0.997869	0.046110	0.0	1.0
Region_Code	381109.0	26.388807	13.229888	0.0	15.0
Previously_Insured	381109.0	0.458210	0.498251	0.0	0.0
Annual_Premium	381109.0	30564.389581	17213.155057	2630.0	24405.0
Policy_Sales_Channel	381109.0	112.034295	54.203995	1.0	29.0
Vintage	381109.0	154.347397	83.671304	10.0	82.0
Response	381109.0	0.122563	0.327936	0.0	0.0

In [12]:
```
df.info()
```

```
<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
```

In [6]:
```
df.shape
```

Out[6]:
```
(381109, 12)
```

In [7]:
```
df.size
```

Out[7]:
```
4573308
```

5.Checking for Missing Values

In [14]:
```
df.isna().sum()
```

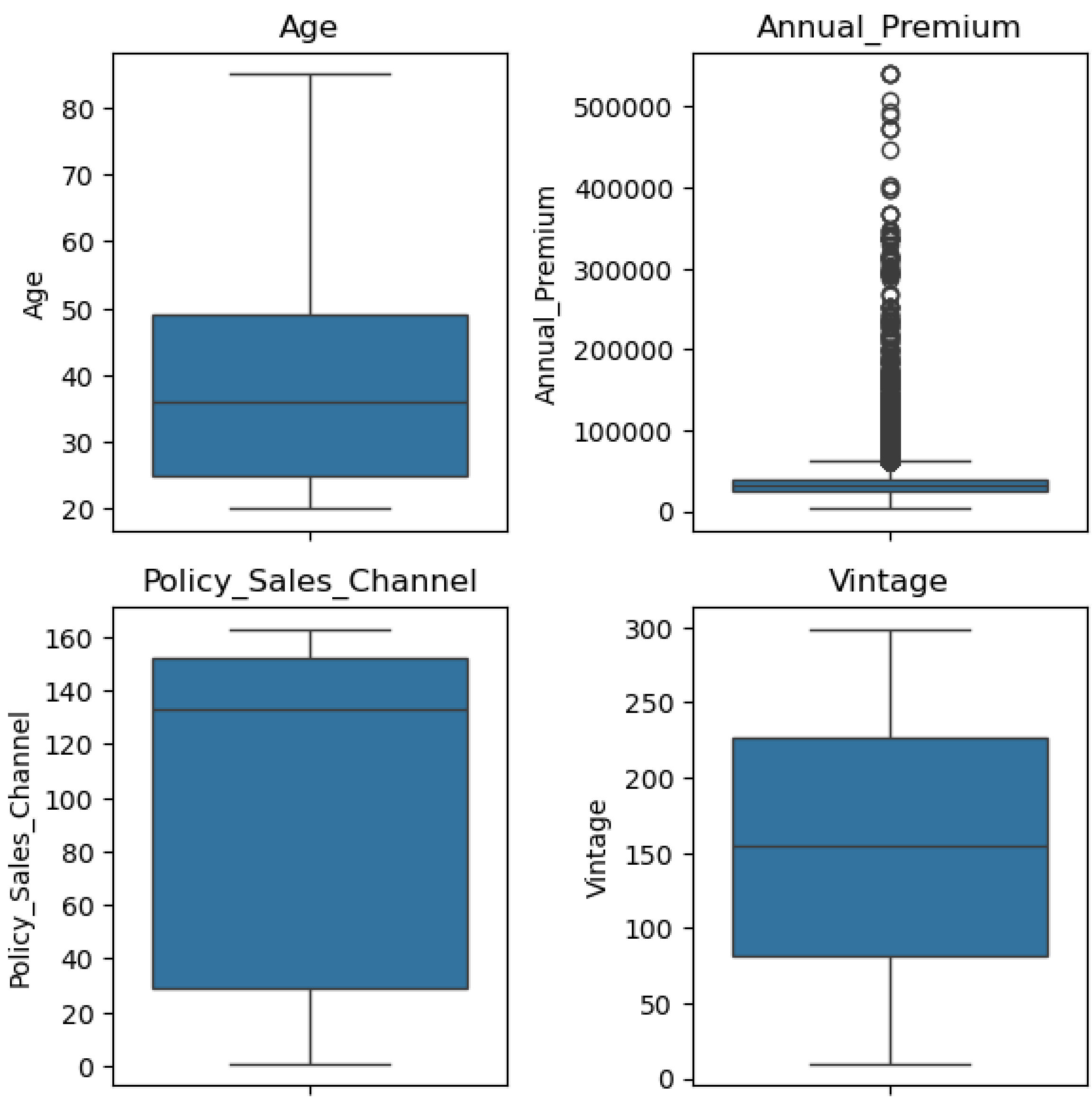
Out[14]:
```
id                      0
Gender                  0
Age                     0
Driving_License         0
Region_Code             0
Previously_Insured      0
Vehicle_Age             0
Vehicle_Damage          0
Annual_Premium          0
Policy_Sales_Channel    0
Vintage                 0
Response                0
dtype: int64
```

6.Checking and Treating outliers

6.1 Checking outliers using Box PLots

In [16]:
```
numeric_columns = ['Age', 'Annual_Premium', 'Policy_Sales_Channel', 'Vintage
plots_per_row = 2
```

```
n_rows = (len(numeric_columns) + plots_per_row - 1) // plots_per_row

fig, axes = plt.subplots(n_rows, plots_per_row, figsize=(6, 3 * n_rows))
axes = axes.flatten()

for i, column in enumerate(numeric_columns):
    sns.boxplot(data=df, y=column, ax=axes[i])
    axes[i].set_title(f'{column}')
    axes[i].set_ylabel(column)

for i in range(len(numeric_columns), len(axes)):
    fig.delaxes(axes[i])

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



6.2 Findings from the Box Plots

- The column **"Annual_Premium"** has potential outliers, which may require further attention, especially if these outliers could impact downstream analysis or model training.

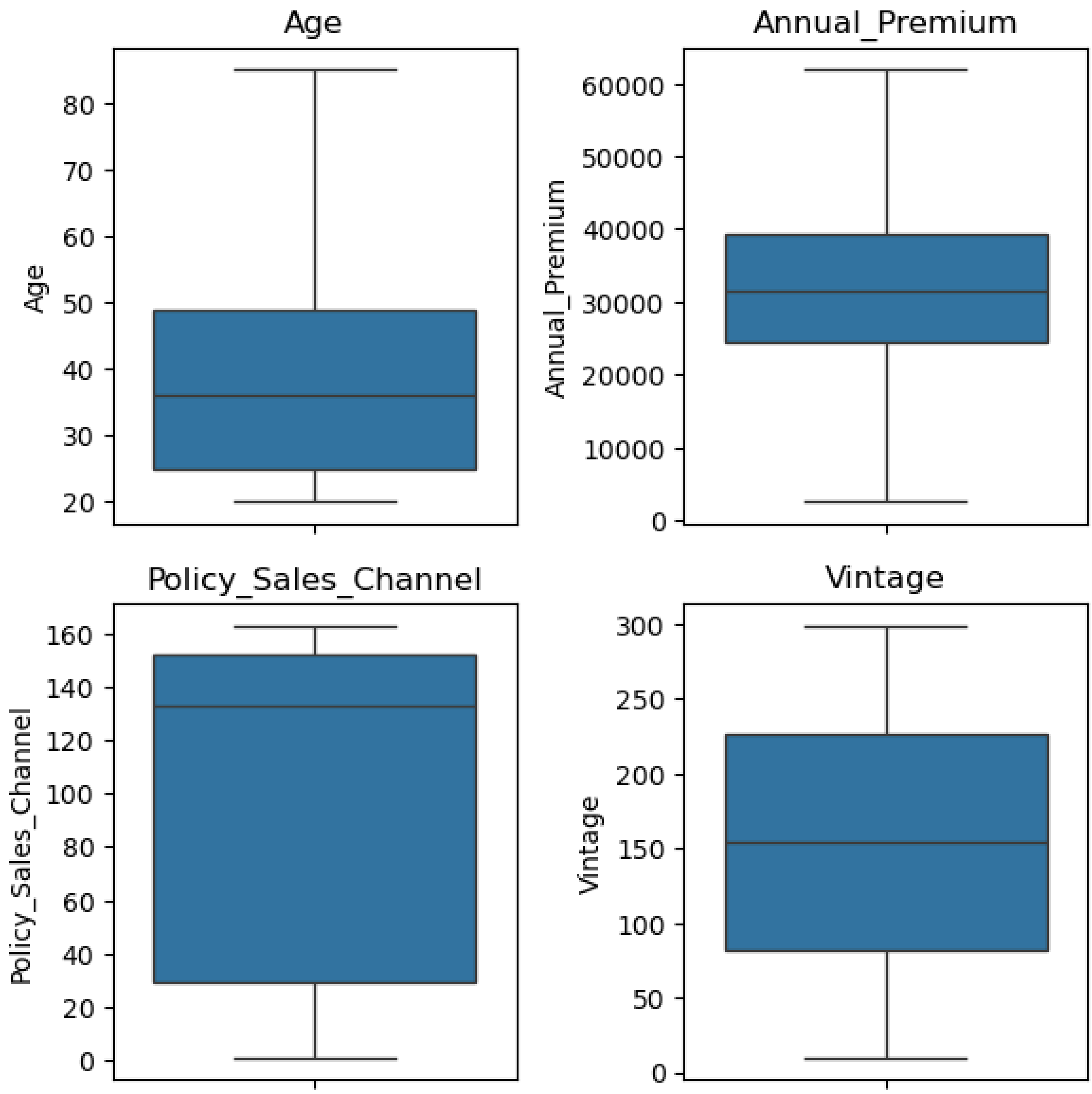
- Other numeric columns, such as **"Age," "Policy_Sales_Channel,"** and **"Vintage,"** do not exhibit notable outliers.

6.3 Treating Outliers in "Annual Premium" Column

In [6]:
```
def replace_outliers(data, column):
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)

    IQR = Q3 - Q1

    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Replace values below lower bound with lower bound and values above upp
    data[column] = data[column].apply(lambda x: lower_bound if x < lower_bou

    return data

data = replace_outliers(df, 'Annual_Premium')
```

6.4 Box PLots after Outliers Treatment

In [50]:
```
numeric_columns = ['Age', 'Annual_Premium', 'Policy_Sales_Channel', 'Vintage
plots_per_row = 2

n_rows = (len(numeric_columns) + plots_per_row - 1) // plots_per_row

fig, axes = plt.subplots(n_rows, plots_per_row, figsize=(6, 3 * n_rows))
axes = axes.flatten()

for i, column in enumerate(numeric_columns):
    sns.boxplot(data=df, y=column, ax=axes[i])
    axes[i].set_title(f'{column}')
    axes[i].set_ylabel(column)

for i in range(len(numeric_columns), len(axes)):
    fig.delaxes(axes[i])

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

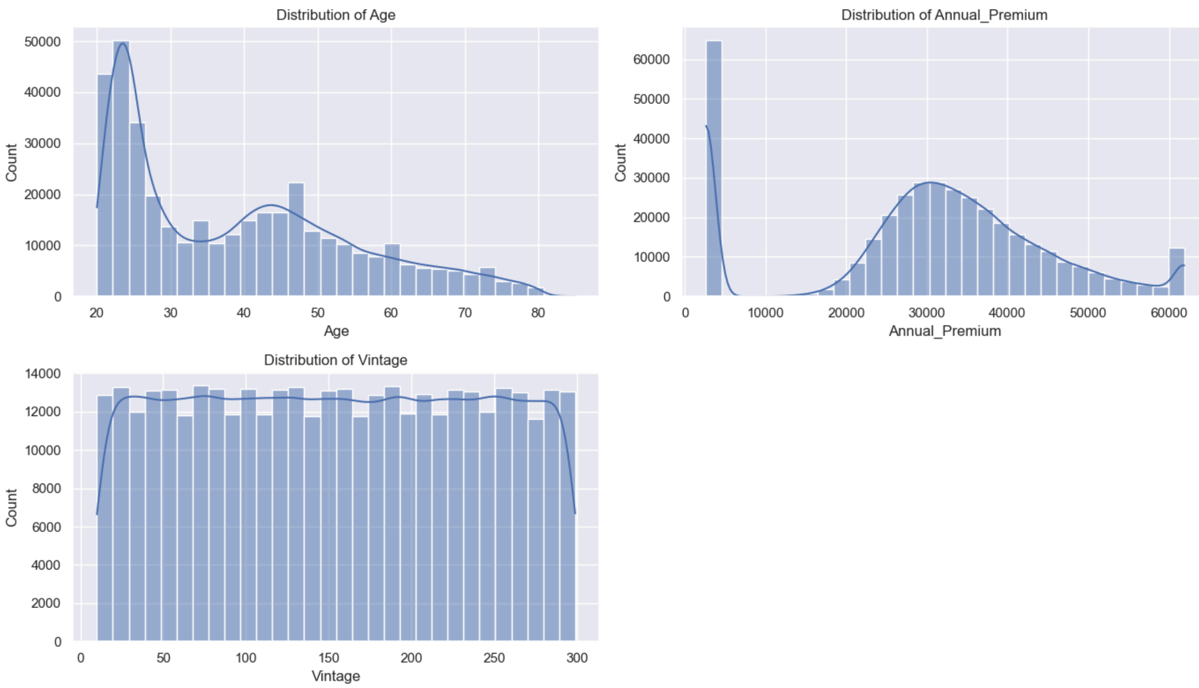


7.Data Visualization

7.1 Histograms for Continuous Variables

In [69]:

```
sns.set(style="darkgrid")

continuous_vars = ['Age', 'Annual_Premium', 'Vintage']
plt.figure(figsize=(14, 8))
for i, column in enumerate(continuous_vars, 1):
    plt.subplot((len(continuous_vars) + 1) // 2, 2, i)
    sns.histplot(df[column], kde=True, bins=30)
    plt.title(f'Distribution of {column}')
plt.tight_layout()
plt.show()
```



Insights from the plots:

Distribution of Age:

- Most policyholders are between 20 and 40 years old.
- There's a slight right skew, indicating a higher proportion of older policyholders.

Distribution of Annual Premium:

- The annual premium distribution is right-skewed, with a significant number of policies having lower premiums.
- There are a few policies with exceptionally high premiums.

Distribution of Vintage:

- The distribution of policy vintage is relatively uniform, with a slight increase in the middle range.
- This indicates a steady growth in the number of policies over time.

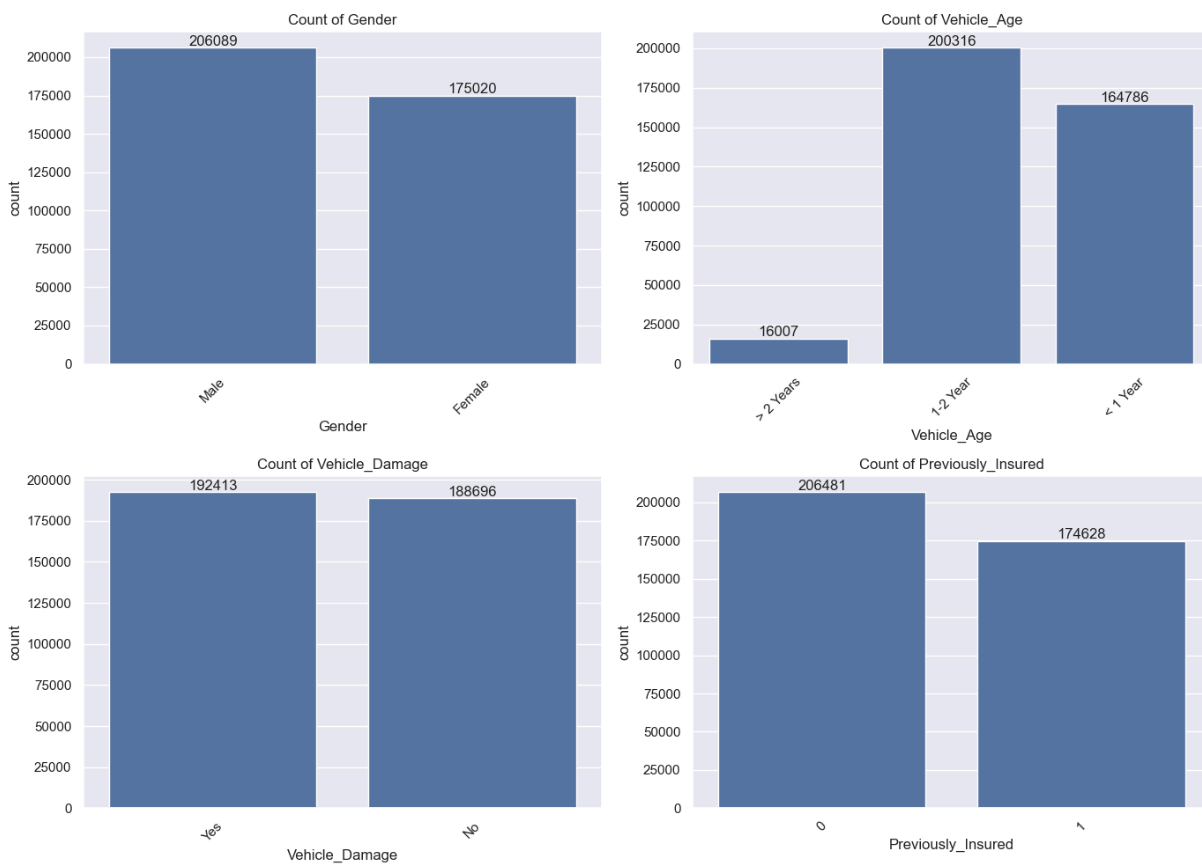
Recommendations:

- **Targeted Marketing:** Focus marketing efforts on the 20-40 age group to attract new customers and retain existing ones.
- **Product Offerings:** Consider offering a wider range of products with varying premium levels to cater to different customer segments.
- **Customer Retention:** Implement strategies to retain long-term customers, especially those with higher vintage.

- **Data-Driven Decision Making:** Continuously analyze the distribution of age, annual premium, and vintage to identify trends and make informed decisions.

7.2 Count Plots for Categorical Variable

In [88]:
```
sns.set(style="darkgrid")
categorical_vars = ['Gender', 'Vehicle_Age', 'Vehicle_Damage', 'Previously_I

plt.figure(figsize=(14, 10))
for i, column in enumerate(categorical_vars, 1):
    plt.subplot((len(categorical_vars) + 1) // 2, 2, i)
    ax = sns.countplot(data=df, x=column)
    plt.title(f'Count of {column}')
    plt.xticks(rotation=45)

    for p in ax.patches:
        ax.annotate(f'{int(p.get_height())}',
                    (p.get_x() + p.get_width() / 2., p.get_height()),
                    ha='center', va='center',
                    xytext=(0, 5), textcoords='offset points')
plt.tight_layout()
plt.show()
```



Insights from the plots:

Count of Gender:

- Majority of the customers are male.

Count of Vehicle Age:

- Most of the vehicles are less than 1 year old.

Count of Vehicle Damage:

- Majority of the vehicles have not faced any damage.

Count of Previously Insured:

- Majority of the customers have not been insured previously.

Recommendations:

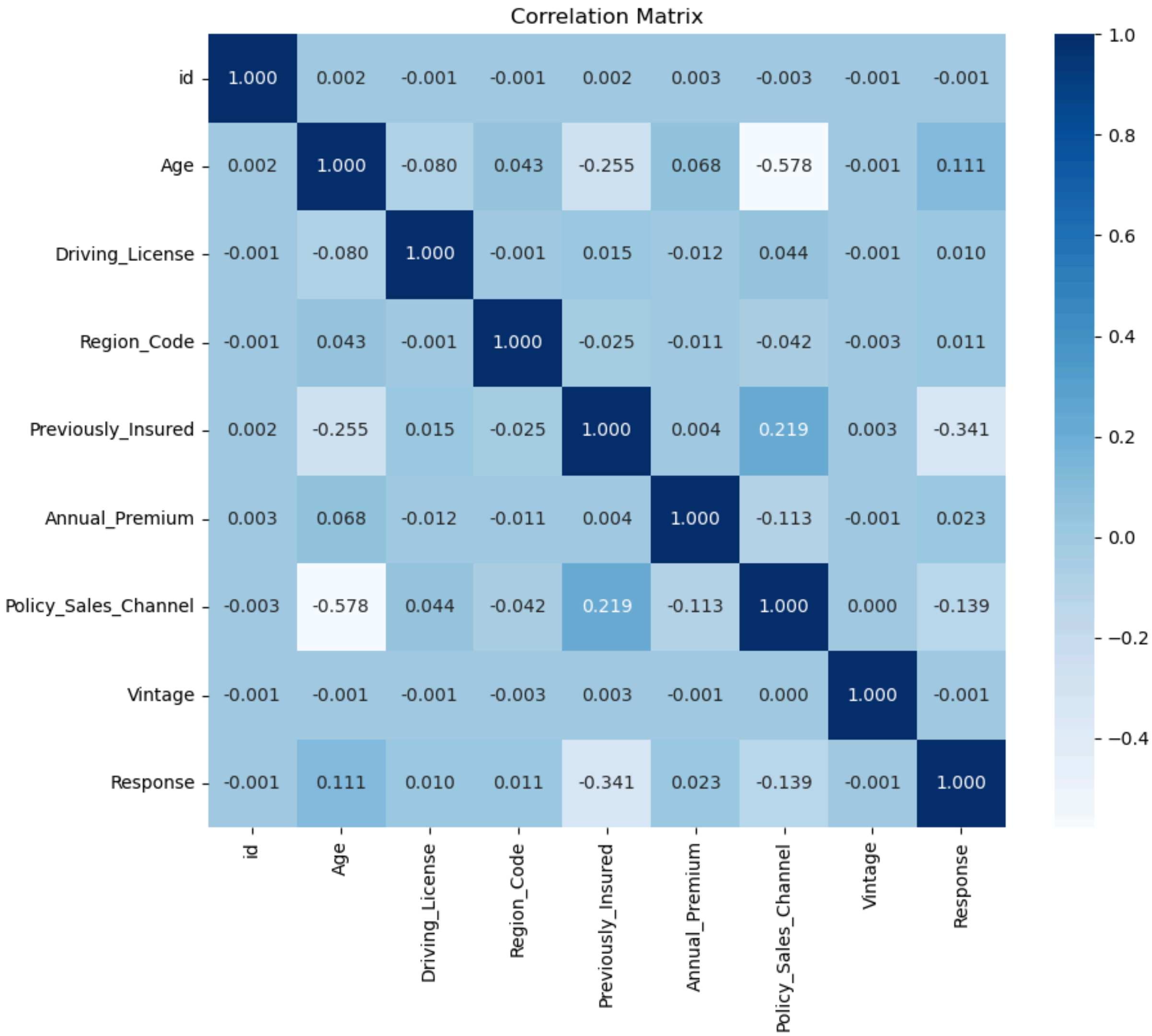
- **Targeted Marketing:** Focus marketing efforts on female customers to increase their share.
- **Product Offerings:** Consider offering specific products for vehicles older than 1 year.
- **Customer Retention:** Focus on retaining customers with previously insured vehicles.
- **Data-Driven Decision Making:** Continuously analyze the distribution of gender, vehicle age, vehicle damage, and previous insurance status to identify trends and make informed decisions.

8. Feature Analysis

8.1 Examining the relationship between features and the target variable

In [8]:

```
df1 = pd.DataFrame(df)
num_df=df1.select_dtypes(include='number')
correlation_matrix = num_df.corr()
plt.figure(figsize=(10,8))
sns.heatmap(correlation_matrix, annot=True, cmap='Blues', fmt=".3f")
plt.title('Correlation Matrix')
plt.show()
```



8.2 insights from the correlation matrix:

Correlation Matrix of Numerical Variables

- **Strong Correlation:** Applicant income and loan amount are strongly positively correlated. This suggests that as income increases, the loan amount also tends to increase.
- **Weak Correlations:** Coapplicant income has a weak positive correlation with loan amount, indicating a minor influence.
- **No Significant Correlations:** Loan amount term and credit history have negligible correlations with other numerical variables.

Recommendations:

- **Risk Assessment:** Consider applicant income as a key factor in assessing loan risk and determining loan amounts.
- **Co-applicant Income:** While co-applicant income has a weak impact, it can still be considered as an additional factor in certain cases.

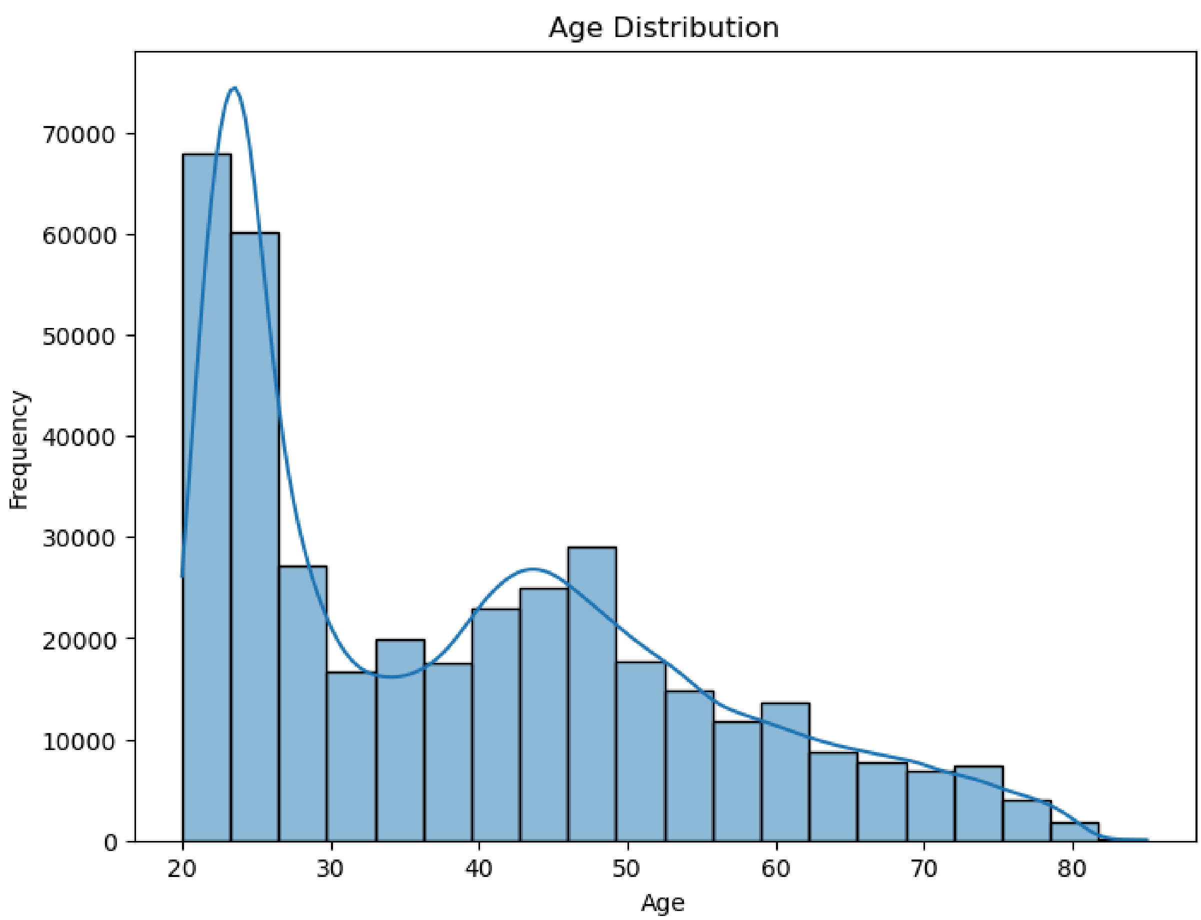
- **Loan Term and Credit History:** Focus on credit history as a primary factor for loan eligibility, while loan term might have a less significant impact.
- **Data-Driven Decisions:** Continuously analyze correlations between variables to refine underwriting and pricing strategies.

9. Age Distribution Analysis

Analyzing age distribution and its impact on insurance claims.

Comparing the proportion of positive responses (Response = 1) across different age groups.

In [43]:
```
plt.figure(figsize=(8, 6))
sns.histplot(df['Age'], kde=True, bins=20)
plt.title('Age Distribution')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



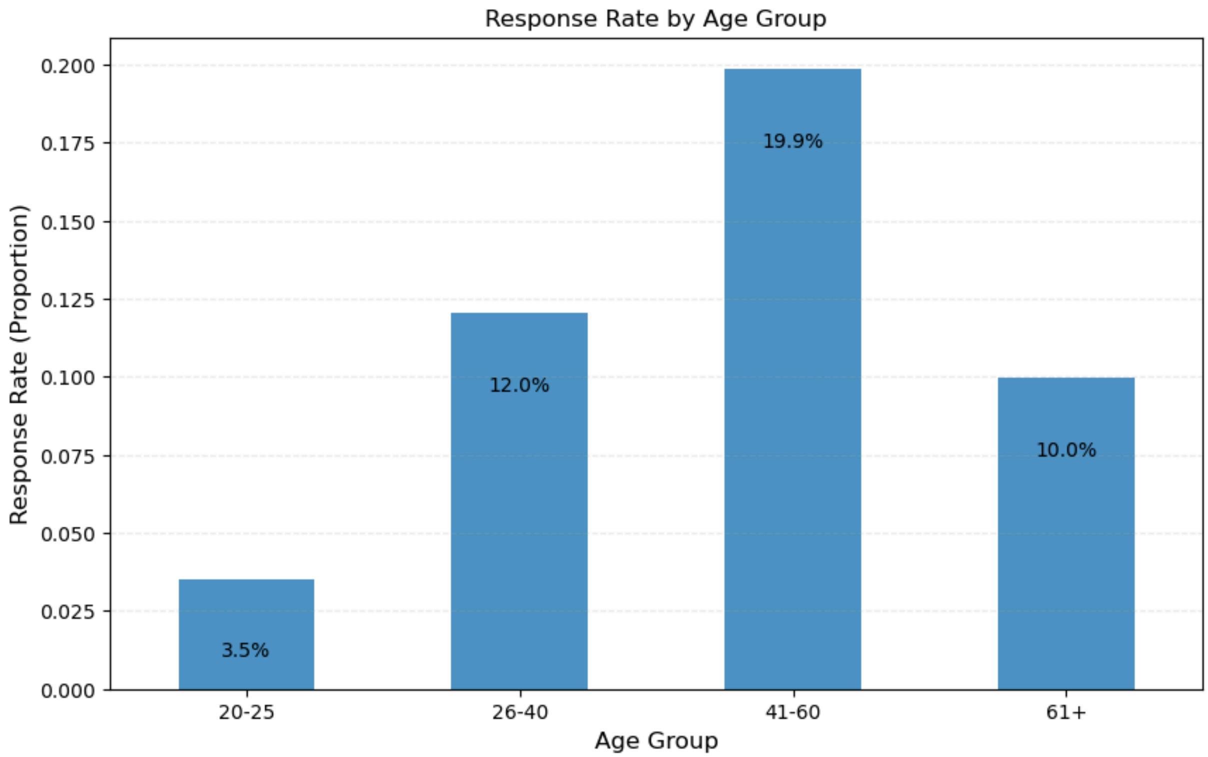
Statistic	Value
Count	381,109
Mean Age	~38.8 years
Median Age	36 years

Statistic	Value
Age Range	20 to 85 years

Distribution:

- Fairly even distribution
- Slight concentration around middle age range (30-50 years)

In [33]:
```
bins = [20, 25, 40, 60, 85]
labels = ['20-25', '26-40', '41-60', '61+']
df['Age_Group'] = pd.cut(df['Age'], bins=bins, labels=labels, right=False)

response_rate_by_age = df.groupby('Age_Group', observed=False)['Response'].m

plt.figure(figsize=(10, 6))
ax = response_rate_by_age.plot(kind='bar', alpha=0.8)

for idx, value in enumerate(response_rate_by_age):
    percentage = f"{value * 100:.1f}%"
    plt.text(
        idx, value - 0.02,
        percentage,
        ha='center', va='top', fontsize=10, color='black'
    )

plt.title("Response Rate by Age Group", fontsize=12)
plt.xlabel("Age Group", fontsize=12)
plt.ylabel("Response Rate (Proportion)", fontsize=12)
plt.xticks(rotation=0)
plt.grid(axis='y', linestyle='--', alpha=0.2)
plt.show()
```



Observations:

- Policyholders aged 41-60 have the highest response rate (~19.9%), indicating they are more likely to engage with insurance claims.
- Younger policyholders (20-25) have the lowest response rate (~3.5%).
- Senior policyholders (61+) also show a reduced response rate compared to the middle-aged group.

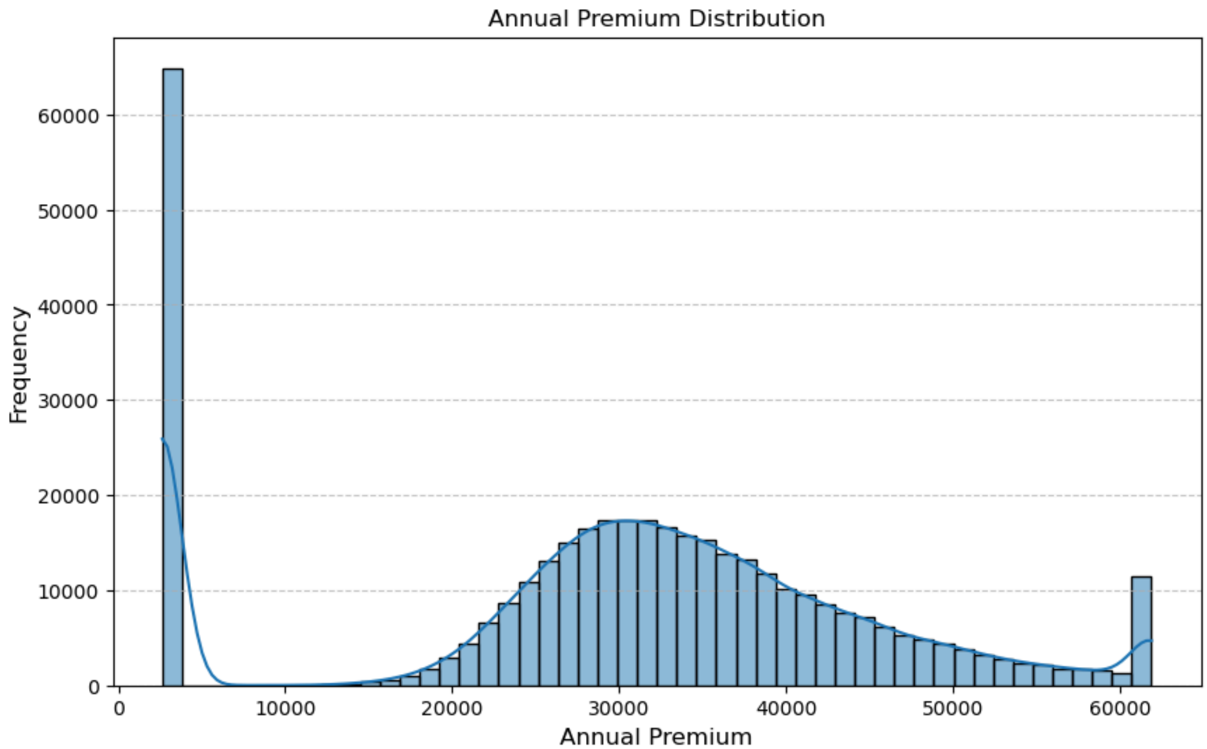
This suggests that middle-aged individuals are more actively engaged in insurance claims, possibly due to greater insurance needs or financial awareness.

10. Premium Analysis

Analyzing the distribution of insurance premiums and their relationship with claim frequencies

In [110…

```
plt.figure(figsize=(10, 6))
sns.histplot(df['Annual_Premium'], bins=50, kde=True)
plt.title("Annual Premium Distribution", fontsize=12)
plt.xlabel("Annual Premium", fontsize=12)
plt.ylabel("Frequency", fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



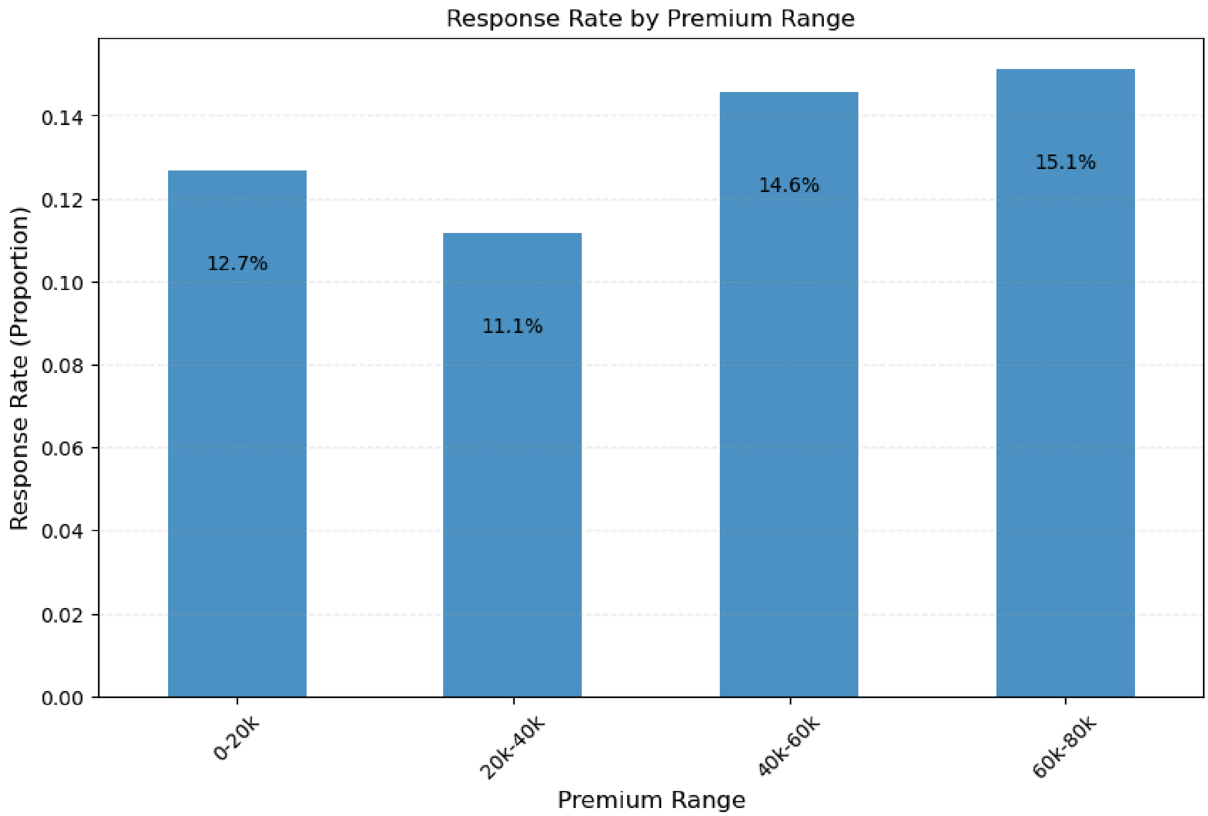
Statistic	Value
Count	381,109
Mean	30,148.17
Standard Deviation	15,476.40
Minimum	2,630
50th Percentile (Median)	31,669
Maximum	61,892.50

Distribution:

- The histogram shows a concentration of premiums between approximately 20,000 and 40,000.

In [31]:
```
max_premium = max(df['Annual_Premium'].max(skipna=True), 100000)
premium_bins = [0, 20000, 40000, 60000, max_premium + 1]
premium_labels = ['0-20k', '20k-40k', '40k-60k', '60k-80k']
df['Premium_Range'] = pd.cut(df['Annual_Premium'], bins=premium_bins, labels

response_rate_by_premium = df.groupby('Premium_Range', observed=False)['Resp

plt.figure(figsize=(10, 6))
ax = response_rate_by_premium.plot(kind='bar', alpha=0.8)

for idx, value in enumerate(response_rate_by_premium):
    percentage = f"{value * 100:.1f}%"
    plt.text(
        idx,
```

```
        value - (0.02 if value > 0.05 else 0.01),
        percentage,
        ha='center',
        va='top',
        fontsize=10,
        color='black'
    )

plt.title("Response Rate by Premium Range", fontsize=12)
plt.xlabel("Premium Range", fontsize=12)
plt.ylabel("Response Rate (Proportion)", fontsize=12)
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.2)
plt.show()
```



Observations:

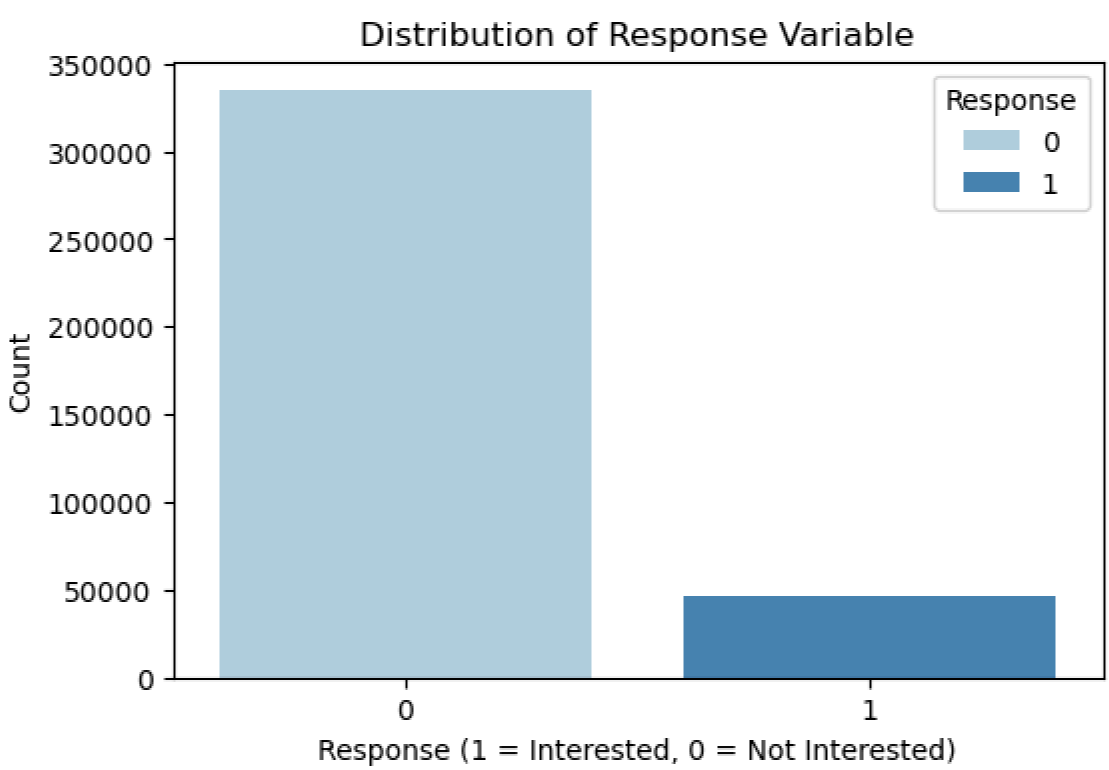
- **0–20k**: ~12.7% claim frequency (highest among lower ranges).
- **20k–40k**: ~11.1% claim frequency.
- **40k–60k**: ~14.6% claim frequency.
- **60k–80k**: ~15.1% claim frequency (peaks here)

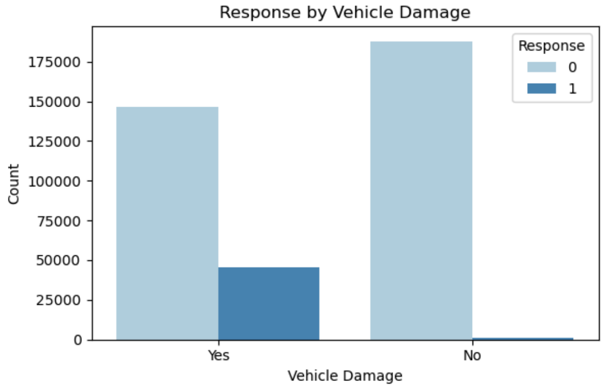
Claim frequency increases with premium range, peaking at 60k-80k. This suggests that more comprehensive policies tend to have higher claim rates.

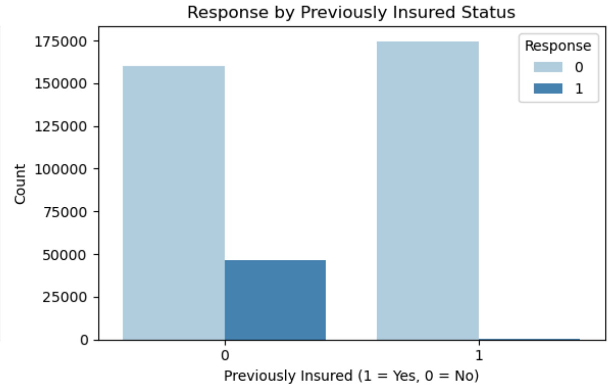
11. Claim Frequencies

The factors contributing to higher claim frequencies using plots to visualize the data.

In [68]:
```
# Plot the distribution of the Response variable
plt.figure(figsize=(6, 4))
sns.countplot(data=data, x='Response', hue='Response', palette='Blues')
plt.title('Distribution of Response Variable')
plt.xlabel('Response (1 = Interested, 0 = Not Interested)')
plt.ylabel('Count')
plt.show()

# Analyze the relationship between Response and other factors
plt.figure(figsize=(18, 4))

# Vehicle_Damage vs Response
plt.subplot(1, 3, 1)
sns.countplot(data=data, x='Vehicle_Damage', hue='Response', palette='Blues'
plt.title('Response by Vehicle Damage')
plt.xlabel('Vehicle Damage')
plt.ylabel('Count')

# Previously_Insured vs Response
plt.subplot(1, 3, 2)
sns.countplot(data=data, x='Previously_Insured', hue='Response', palette='Bl
plt.title('Response by Previously Insured Status')
plt.xlabel('Previously Insured (1 = Yes, 0 = No)')
plt.ylabel('Count')

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





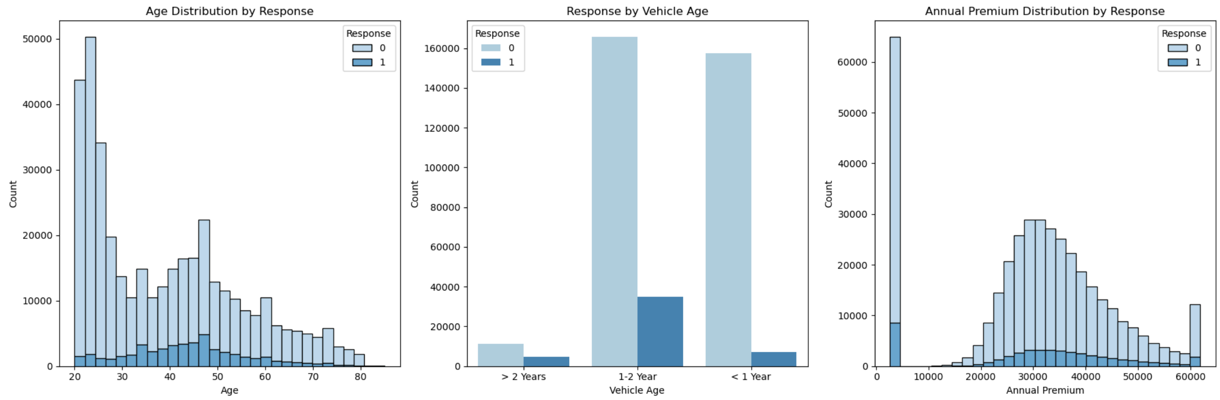


Observations from the Plots:

- **Distribution of Response:** The dataset is imbalanced, with significantly more instances where the policyholder is not interested (Response = 0).
- **Vehicle Damage vs Response:** Policyholders with a history of vehicle damage (Vehicle_Damage = Yes) are more likely to respond positively (Response = 1).
- **Previously Insured vs Response:** Policyholders not previously insured (Previously_Insured = 0) are more likely to respond positively.

Analyzing the effects of Age, Vehicle_Age, and Annual_Premium on claim frequency.

In [43]:
```
plt.figure(figsize=(18, 6))

# Age distribution by Response
plt.subplot(1, 3, 1)
sns.histplot(data=data, x='Age', hue='Response', multiple='stack', palette='
plt.title('Age Distribution by Response')
plt.xlabel('Age')
plt.ylabel('Count')

# Vehicle_Age vs Response
plt.subplot(1, 3, 2)
sns.countplot(data=data, x='Vehicle_Age', hue='Response', palette='Blues')
plt.title('Response by Vehicle Age')
plt.xlabel('Vehicle Age')
plt.ylabel('Count')

# Annual_Premium distribution by Response
plt.subplot(1, 3, 3)
sns.histplot(data=data, x='Annual_Premium', hue='Response', multiple='stack'
plt.title('Annual Premium Distribution by Response')
plt.xlabel('Annual Premium')
plt.ylabel('Count')

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



Observations from the Plots:

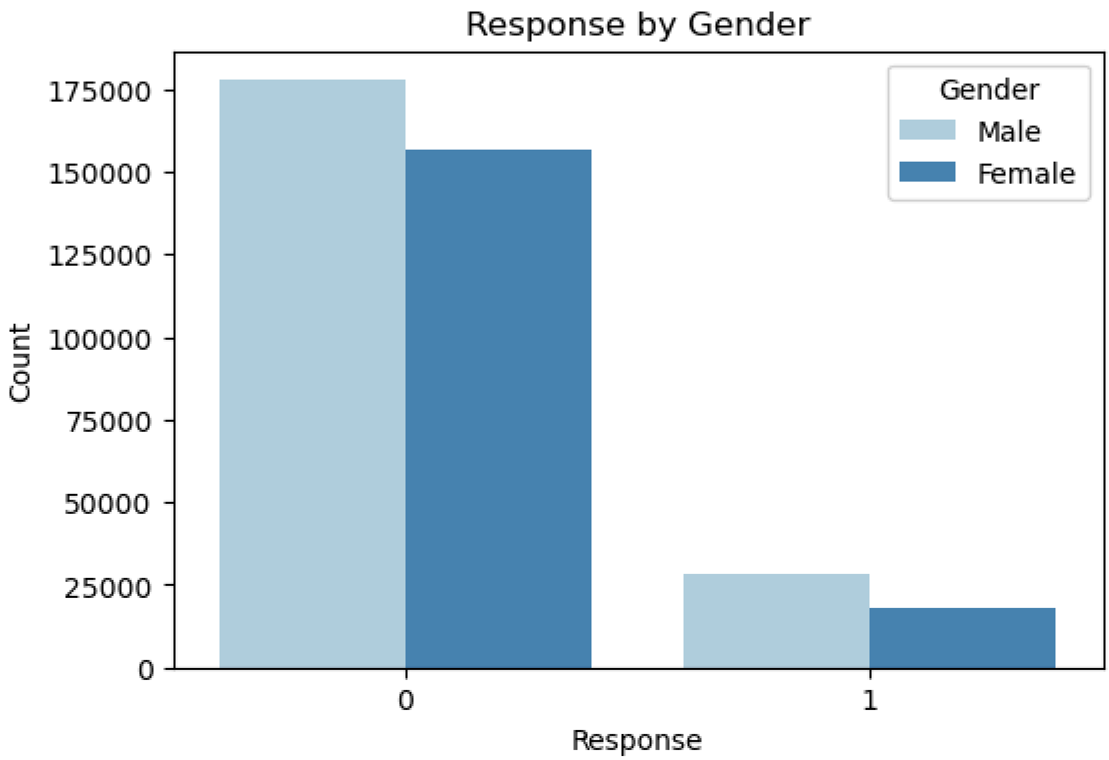
- **Age Distribution by Response:** Policyholders aged between 20-40 years show a higher interest (Response = 1). Interest in policies declines significantly for policyholders aged above 50.
- **Response by Vehicle Age:** Vehicles older than 2 years (> 2 Years) are associated with a higher number of interested responses. Newer vehicles (< 1 Year) have fewer interested responses.
- **Annual Premium Distribution by Response:** Interested responses (Response = 1) are more concentrated in the lower premium range (approximately below 50,000). Higher premiums show a declining trend in interest.

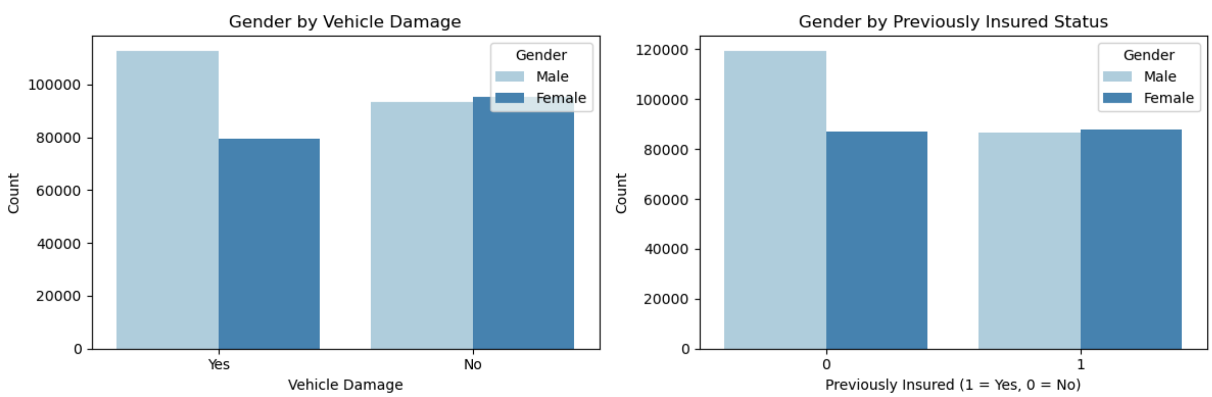
12. Gender Analysis

Investigating the role of gender in insurance claims

In [72]:
```
# Plot the distribution of the Gender variable
plt.figure(figsize=(6, 4))
sns.countplot(data=data, x='Response', hue='Gender', palette='Blues')
plt.title('Response by Gender')
plt.xlabel('Response')
plt.ylabel('Count')
plt.show()

# Analyze the relationship between Response and other factors
plt.figure(figsize=(18, 4))

# Vehicle_Damage vs Response
plt.subplot(1, 3, 1)
sns.countplot(data=data, x='Vehicle_Damage', hue='Gender', palette='Blues')
plt.title('Gender by Vehicle Damage')
plt.xlabel('Vehicle Damage')
plt.ylabel('Count')

# Previously_Insured vs Response
plt.subplot(1, 3, 2)
sns.countplot(data=data, x='Previously_Insured', hue='Gender', palette='Blue
```

```
plt.title('Gender by Previously Insured Status')
plt.xlabel('Previously Insured (1 = Yes, 0 = No)')
plt.ylabel('Count')

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





Observations from the Plots:

1. **Response by Gender**:
    - Most individuals did not respond positively (Response = 0).
    - Males have a slightly higher count than females in both response categories.
2. **Gender by Vehicle Damage**:
    - There are more males with vehicle damage (Yes) than females.

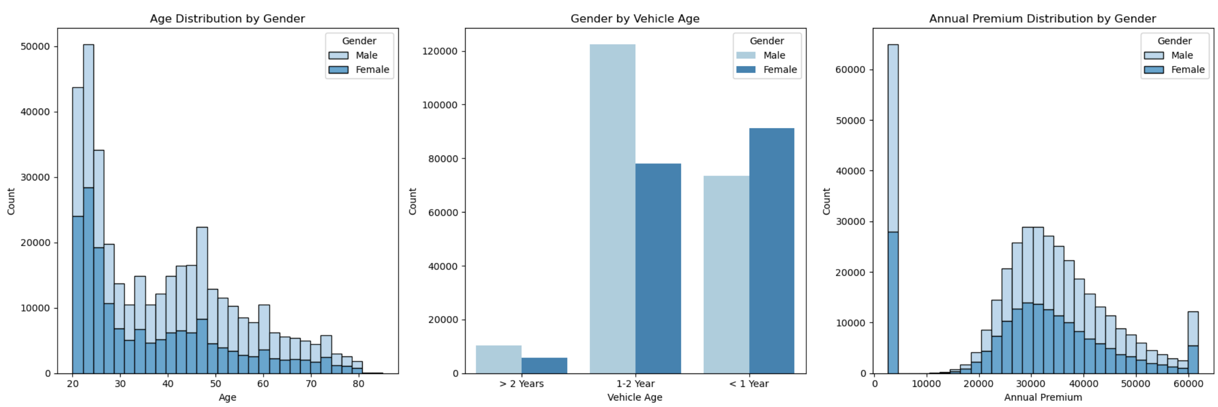
- Females slightly outnumber males among those without vehicle damage (No).

3. **Gender by Previously Insured Status**:

   - Males are more likely to be uninsured (Previously Insured = 0) than females.
   - Among those who are insured (Previously Insured = 1), the numbers of males and females are almost equal.

Distribution of Demographic and Vehicle Attributes by Gender

In [82]:
```
plt.figure(figsize=(18, 6))

plt.subplot(1, 3, 1)
sns.histplot(data=data, x='Age', hue='Gender', multiple='stack', palette='Bl
plt.title('Age Distribution by Gender')
plt.xlabel('Age')
plt.ylabel('Count')

plt.subplot(1, 3, 2)
sns.countplot(data=data, x='Vehicle_Age', hue='Gender', palette='Blues')
plt.title('Gender by Vehicle Age')
plt.xlabel('Vehicle Age')
plt.ylabel('Count')

plt.subplot(1, 3, 3)
sns.histplot(data=data, x='Annual_Premium', hue='Gender', multiple='stack',
plt.title('Annual Premium Distribution by Gender')
plt.xlabel('Annual Premium')
plt.ylabel('Count')

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



Observations from the Plots:

- **Age Distribution by Gender:**

  - The distribution of ages is similar for both genders, with a peak in the 25-40 age range.

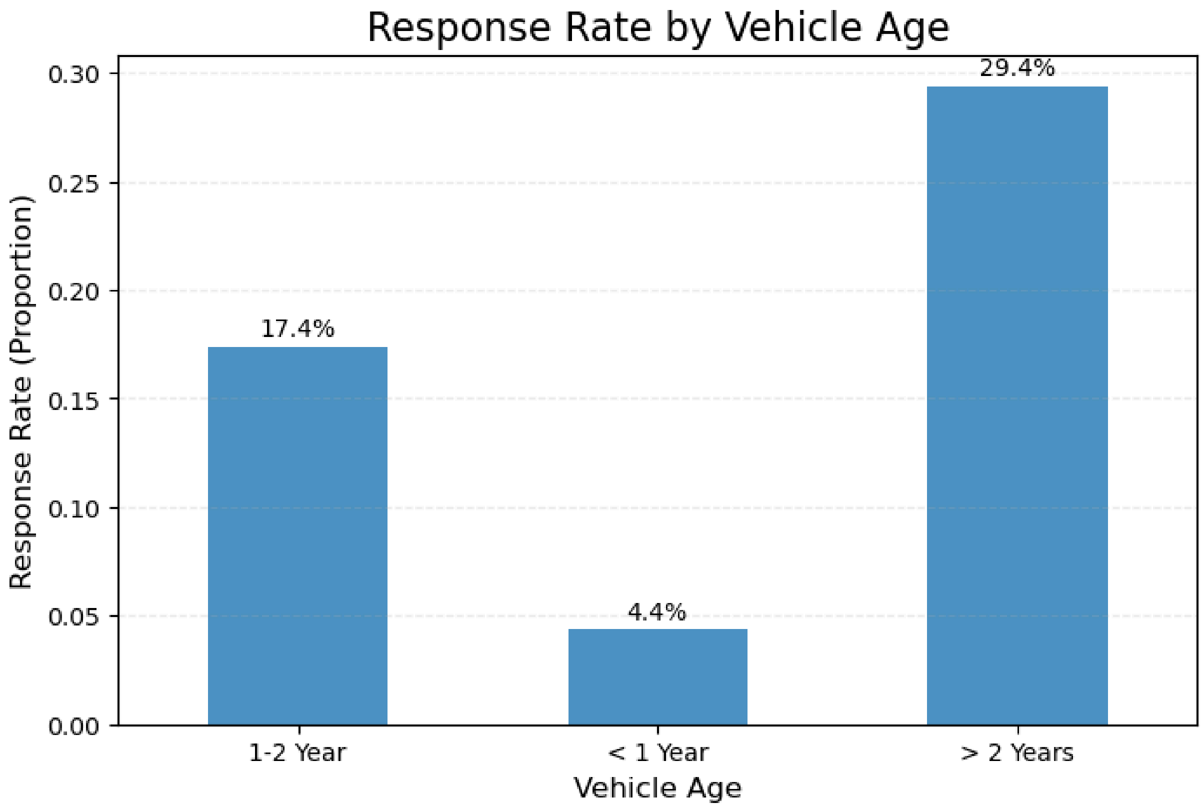
- There are slightly more female policyholders in the younger age groups (20-30) and slightly more male policyholders in the older age groups (50-70).
- **Gender by Vehicle Age:**
  - Both genders have a similar distribution of vehicle ages.
  - Most policyholders have vehicles that are 1-2 years old, followed by vehicles older than 2 years.
  - The proportion of vehicles less than 1 year old is relatively small for both genders.
- **Annual Premium Distribution by Gender:**
  - The distribution of annual premiums is similar for both genders, with a peak around the 25,000-30,000 range.
  - There is a long tail towards higher premiums, indicating a significant number of policyholders with higher premiums.
  - The distribution is slightly skewed to the right for both genders.

13. Vehicle Age and Claims

Examining the impact of vehicle age on the likelihood of a claim

In [35]:

```
plt.figure(figsize=(8, 5))
bars = response_rate_by_vehicle_age.plot(kind='bar', alpha=0.8)
for bar in bars.containers:
    for rect in bar:
        height = rect.get_height()
        plt.text(
            rect.get_x() + rect.get_width() / 2,
            height + 0.005,
            f'{height:.1%}',
            ha='center',
            fontsize=10
        )

plt.title("Response Rate by Vehicle Age", fontsize=16)
plt.xlabel("Vehicle Age", fontsize=12)
plt.ylabel("Response Rate (Proportion)", fontsize=12)
plt.xticks(rotation=0)
plt.grid(axis='y', linestyle='--', alpha=0.2)
plt.show()
```



Observations from the Plot:

- **Vehicle Age and Response Rate:** There's a clear correlation between vehicle age and the response rate.
- **Higher Response for Older Vehicles:** Policyholders with vehicles older than 2 years have the highest response rate (29.4%).
- **Lower Response for Newer Vehicles:** Policyholders with newer vehicles (less than 1 year old) have the lowest response rate (4.4%).
- **Moderate Response for 1-2 Year Old Vehicles:** Those with vehicles aged 1-2 years have a moderate response rate (17.4%).

This suggests that older vehicles might have a higher likelihood of needing insurance claims or replacements, leading to a higher interest in insurance policies.

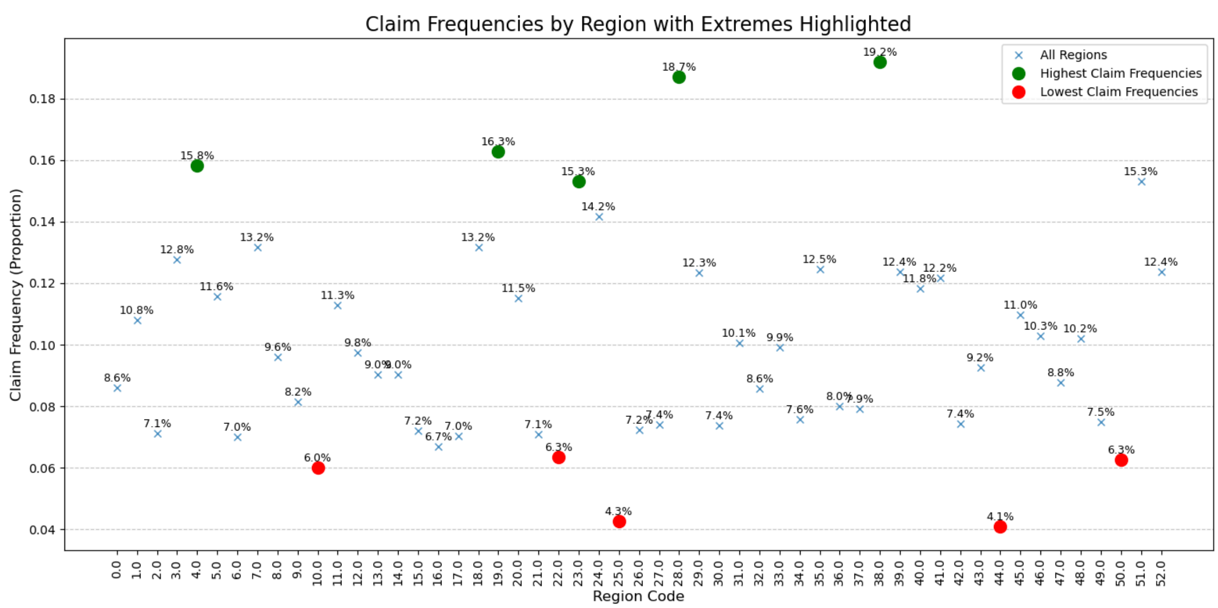
14. Region-wise Analysis

Analyzing regional patterns in insurance claims

In [68]:

```
regional_claim_frequencies = df.groupby('Region_Code')['Response'].mean()

plt.figure(figsize=(14, 7))

plt.plot(regional_claim_frequencies.index.astype(str), regional_claim_freque
```

```
plt.plot(highest_regions.index.astype(str), highest_regions, 'o', color='gre
plt.plot(lowest_regions.index.astype(str), lowest_regions, 'o', color='red',

for idx in regional_claim_frequencies.index:
    plt.text(
        str(idx), regional_claim_frequencies[idx] + 0.002,
        f'{regional_claim_frequencies[idx]:.1%}',
        ha='center', fontsize=9
    )

plt.title("Claim Frequencies by Region with Extremes Highlighted", fontsize=
plt.xlabel("Region Code", fontsize=12)
plt.ylabel("Claim Frequency (Proportion)", fontsize=12)
plt.xticks(rotation=90)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.legend()
plt.tight_layout()
plt.show()
```



Top 5 Regions with Highest Claim Frequencies:

- Region Code 38: 19.2%
- Region Code 28: 18.7%
- Region Code 19: 16.3%
- Region Code 4: 15.8%
- Region Code 23: 15.3%

Top 5 Regions with Lowest Claim Frequencies:

- Region Code 44: 4.1%
- Region Code 25: 4.3%
- Region Code 10: 6.0%
- Region Code 50: 6.3%
- Region Code 22: 6.3%

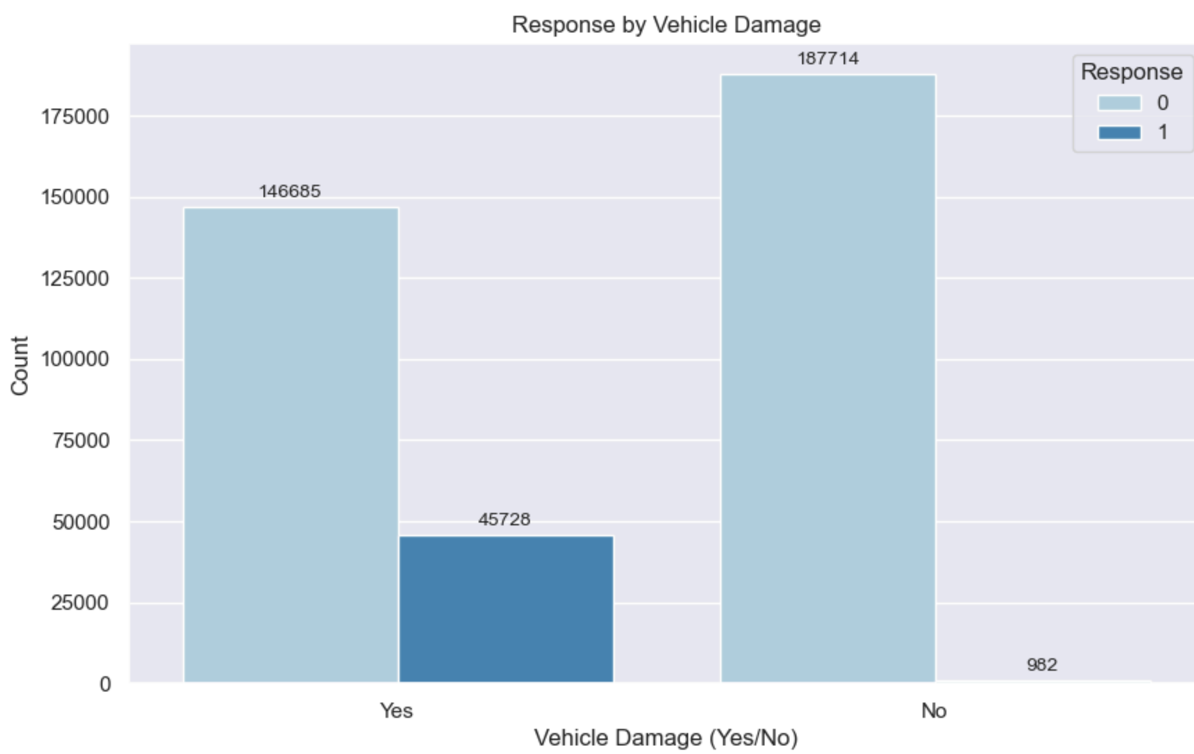
Observations from the Plot:

- **Regional Variation in Claim Frequencies:** There is significant variation in claim frequencies across different regions.
- **High Claim Regions:** A few regions (highlighted in green) exhibit significantly higher claim frequencies compared to the average.
- **Low Claim Regions:** Similarly, a few regions (highlighted in red) have substantially lower claim frequencies.
- **Majority of Regions:** Most regions have claim frequencies clustered around a certain range, indicating a general trend.

15. Claim Frequency by Vehicle Damage Analysis

Investigating the relationship between vehicle damage and claim frequencies

In [43]:
```
plt.figure(figsize=(10, 6))
ax = sns.countplot(data=data, x='Vehicle_Damage', hue='Response', palette='B
plt.title('Response by Vehicle Damage')
plt.xlabel('Vehicle Damage (Yes/No)')
plt.ylabel('Count')

for container in ax.containers:
    ax.bar_label(container, label_type='edge', fontsize=10, padding=3)

plt.show()
```

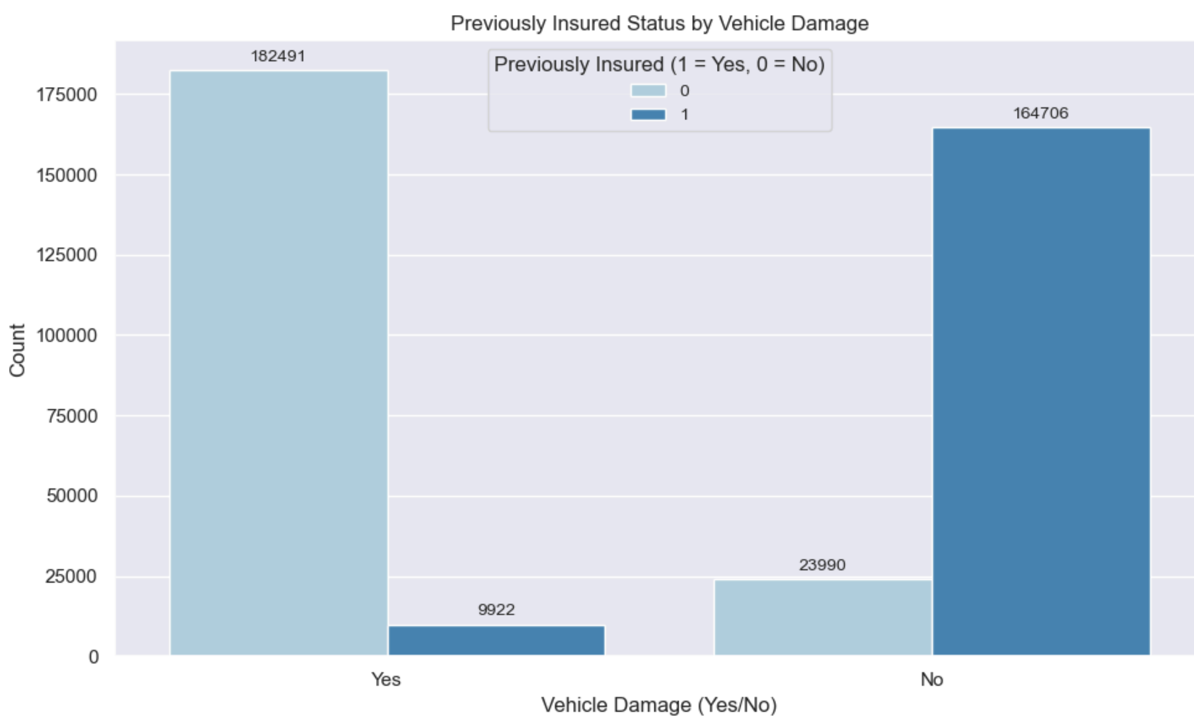


Observations from the Plot:

- **Impact of Vehicle Damage on Response:** There is a clear relationship between vehicle damage history and the response rate.
- **Higher Response with Vehicle Damage:** Policyholders with a history of vehicle damage (Yes) are significantly more likely to respond positively (Response = 1).
- **Lower Response without Vehicle Damage:** Those without a history of vehicle damage (No) have a lower response rate.

This suggests that individuals with previous vehicle damage claims might be more proactive in seeking insurance coverage, possibly due to concerns about future incidents.

In [41]:
```
plt.figure(figsize=(10, 6))
ax = sns.countplot(data=data, x='Vehicle_Damage', hue='Previously_Insured',

for container in ax.containers:
    ax.bar_label(container, label_type='edge', fontsize=10, padding=3)

plt.title('Previously Insured Status by Vehicle Damage', fontsize=12)
plt.xlabel('Vehicle Damage (Yes/No)', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.legend(title='Previously Insured (1 = Yes, 0 = No)', fontsize=10)
plt.tight_layout()

plt.show()
```



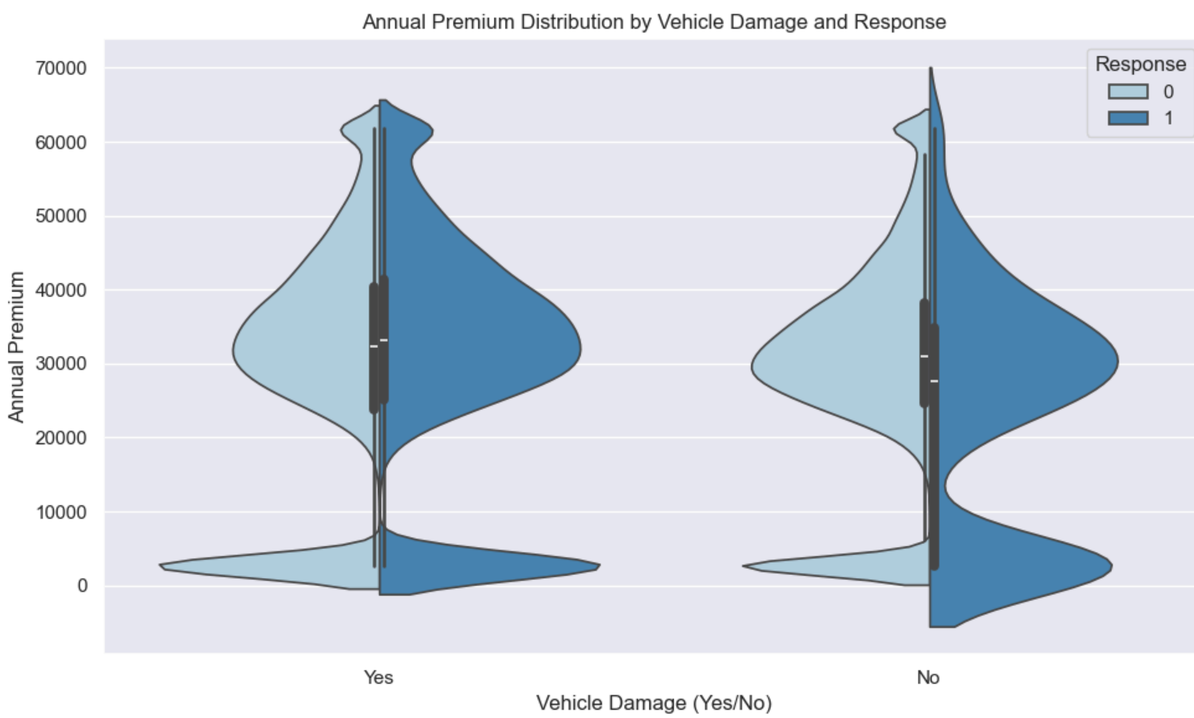
Observations from the Plot:

- **Relationship between Previous Insurance and Vehicle Damage:** There is a clear interaction between whether a policyholder was previously insured and their vehicle damage history.

- **Higher Previous Insurance for No Damage:** Policyholders without a history of vehicle damage (No) are more likely to have been previously insured (1).
- **Lower Previous Insurance for Vehicle Damage:** Those with a history of vehicle damage (Yes) are less likely to have been previously insured (0).

This suggests that a history of vehicle damage might negatively impact the likelihood of obtaining insurance coverage in the future.

In [49]:
```
plt.figure(figsize=(10, 6))
sns.violinplot(data=df, x='Vehicle_Damage', y='Annual_Premium', hue='Respons

# Customize the plot
plt.title('Annual Premium Distribution by Vehicle Damage and Response')
plt.xlabel('Vehicle Damage (Yes/No)')
plt.ylabel('Annual Premium')
plt.legend(title='Response', loc='upper right')
plt.tight_layout()

plt.show()
```



Observations from the Plot:

- **Annual Premium Distribution by Vehicle Damage and Response:** The plot shows how annual premiums vary based on vehicle damage history and the policyholder's response.
- **Higher Premiums for Damaged Vehicles:** In general, policyholders with vehicles that have been damaged tend to have higher annual premiums

compared to those without damage.

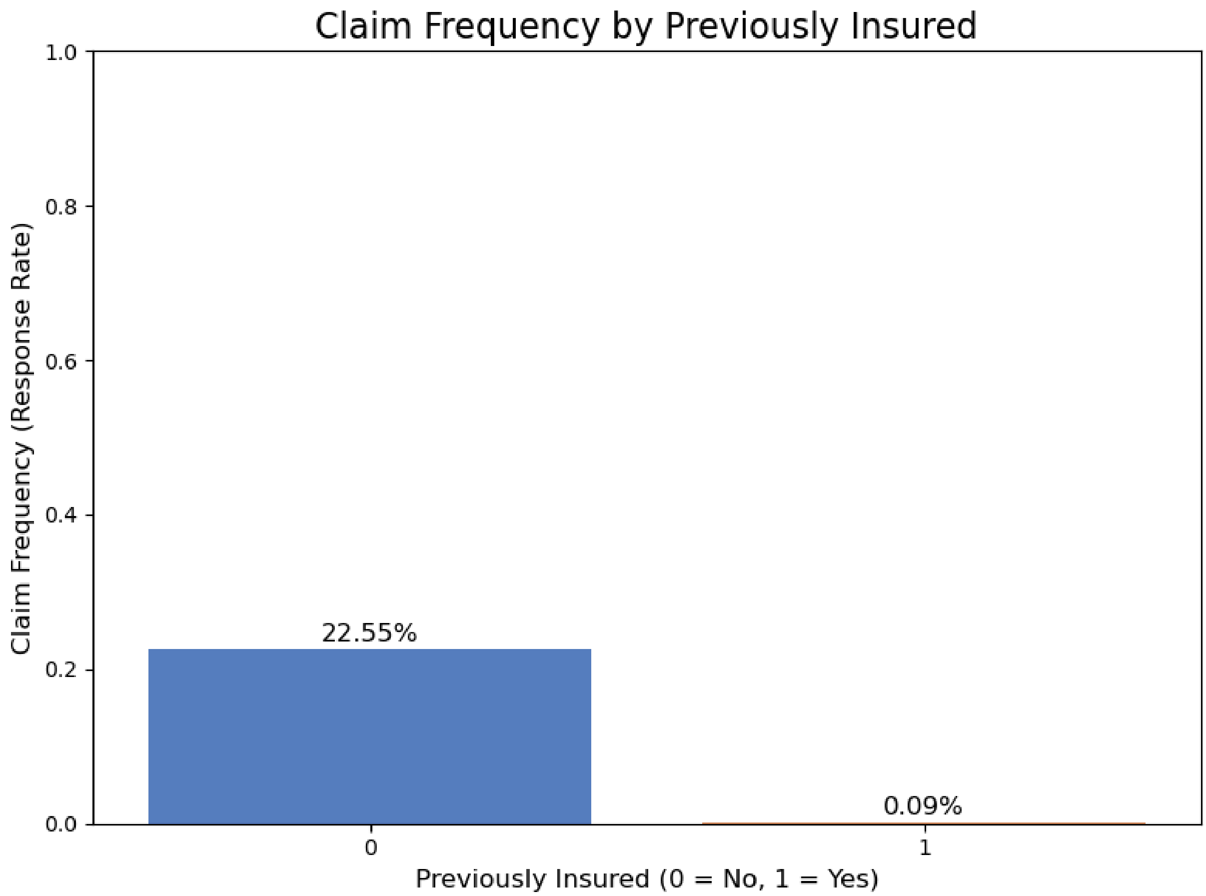
- **Premium Distribution Differences by Response:** The distribution of premiums differs between policyholders who responded positively (Response = 1) and those who didn't (Response = 0).
  - **Positive Response:** Policyholders who responded positively tend to have a wider range of annual premiums, with some having very high premiums.
  - **Negative Response:** Those who didn't respond tend to have a more concentrated distribution of premiums, with a majority falling in the lower to mid-range.

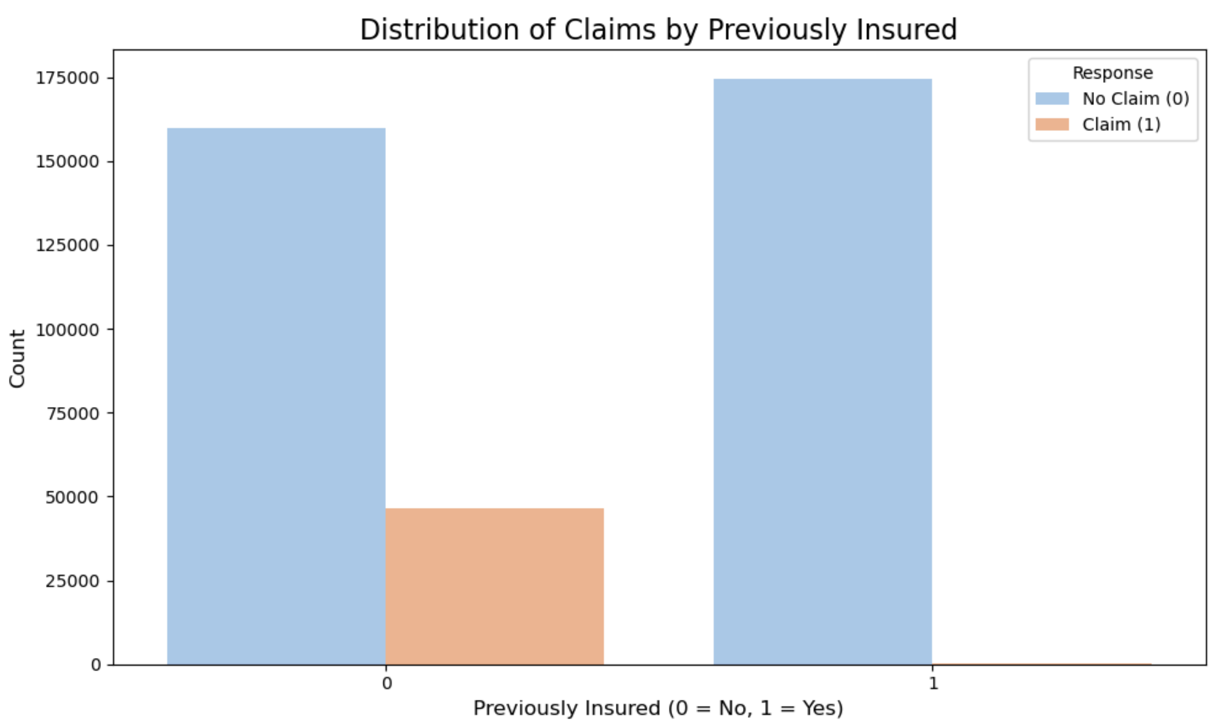
This suggests that factors like vehicle damage history and the policyholder's interest in the policy can significantly influence the annual premium charged.

16. Customer Loyalty Analysis

Analyzing if the number of policies held by a customer influences claim likelihood.

In [28]:
```
insured_response_rate = df.groupby('Previously_Insured')['Response'].mean().

# Bar Plot for Claim Frequency
plt.figure(figsize=(8, 6))
bar_plot = sns.barplot(x='Previously_Insured', y='Response',hue='Previously_

for index, row in insured_response_rate.iterrows():
    bar_plot.text(x=index, y=row['Response'] + 0.01,
                  s=f"{row['Response']:.2%}",
                  ha='center', fontsize=12, color='black')

plt.title("Claim Frequency by Previously Insured", fontsize=12)
plt.xlabel("Previously Insured (0 = No, 1 = Yes)", fontsize=12)
plt.ylabel("Claim Frequency (Response Rate)", fontsize=12)
plt.ylim(0, 1)
plt.tight_layout()
plt.show()

# Count Plot for Claims by Previously Insured
plt.figure(figsize=(10, 6))
sns.countplot(x='Previously_Insured', hue='Response', data=data, palette="Bl
plt.title("Distribution of Claims by Previously Insured", fontsize=12)
plt.xlabel("Previously Insured (0 = No, 1 = Yes)", fontsize=12)
plt.ylabel("Count", fontsize=12)
plt.legend(title="Response", loc="upper right", labels=["No Claim (0)", "Cla
plt.tight_layout()
plt.show()
```





Observations from the Plot:

Claim Frequency by Previously Insured:

- **Low Claim Frequency for Previously Insured:** Policyholders who were previously insured have a significantly lower claim frequency (0.09%).

- **Higher Claim Frequency for Non-Previously Insured:** Those who were not previously insured have a much higher claim frequency (22.55%).

Distribution of Claims by Previously Insured:

- **Fewer Claims for Previously Insured:** The number of claims is significantly lower for previously insured policyholders.
- **More Claims for Non-Previously Insured:** A larger number of claims are associated with policyholders who were not previously insured.

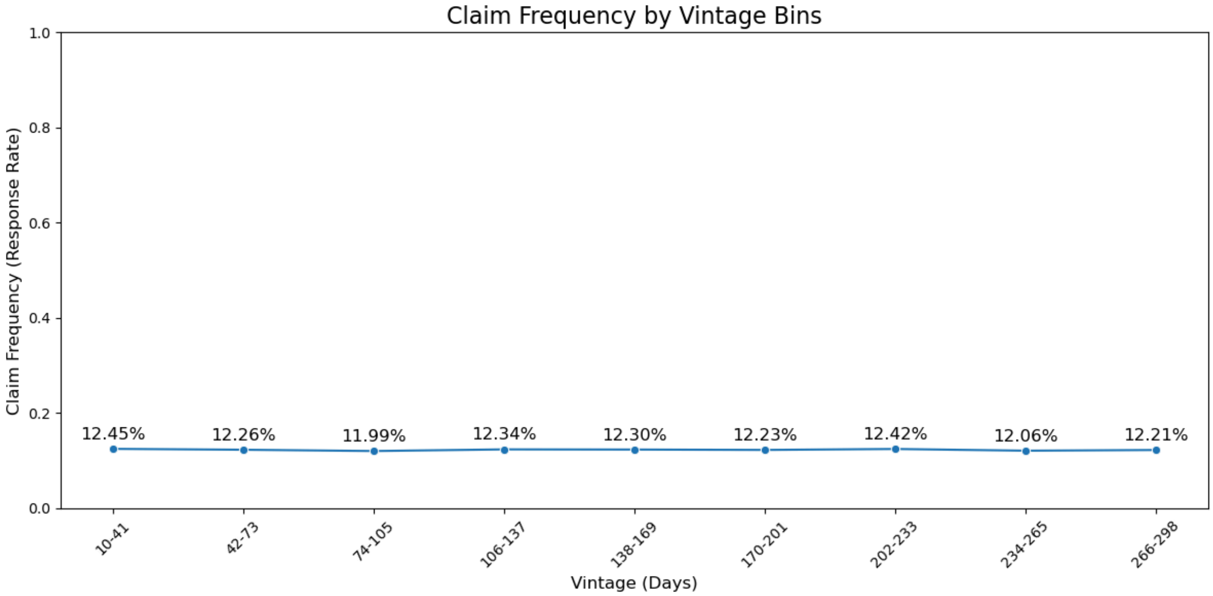
Overall Interpretation:

These plots suggest that having a history of insurance can positively impact a policyholder's claim behavior. Previously insured individuals are less likely to file claims, potentially indicating responsible driving habits or a lower risk profile.

17. Time Analysis

Exploring temporal patterns in insurance claims

In [90]:
```
bins = np.linspace(10, 299, num=10)  # Adjust the number of bins as needed
labels = [f"{int(bins[i])}-{int(bins[i+1]-1)}" for i in range(len(bins)-1)]
data['Vintage_Binned'] = pd.cut(data['Vintage'], bins=bins, labels=labels, r

# Calculate claim frequency by Vintage bins
vintage_claim_rate = data.groupby('Vintage_Binned', observed=False)['Respons

# Line plot with annotations
plt.figure(figsize=(12, 6))
line_plot = sns.lineplot(x='Vintage_Binned', y='Response', data=vintage_clai

# Add annotations to the points
for index, row in vintage_claim_rate.iterrows():
    plt.text(index, row['Response'] + 0.02, f"{row['Response']:.2%}",
             ha='center', fontsize=12, color='black')

# Plot settings
plt.title("Claim Frequency by Vintage Bins", fontsize=16)
plt.xlabel("Vintage (Days)", fontsize=12)
plt.ylabel("Claim Frequency (Response Rate)", fontsize=12)
plt.xticks(rotation=45)
plt.ylim(0, 1)  # Set y-axis to percentage scale
plt.tight_layout()
plt.show()
```



Observations from the Plot:

- **Claim Frequency by Vintage:** The plot shows how the claim frequency (response rate) varies across different vintage bins (days since the policy was taken).
- **Relatively Stable Claim Frequency:** The claim frequency remains relatively stable across all vintage bins, with minor fluctuations.
- **No Significant Trend:** There is no clear upward or downward trend in claim frequency as the vintage increases.

This suggests that the time since a policy was taken does not have a significant impact on the likelihood of a claim. Policyholders with both new and older policies exhibit similar claim patterns.

Vehicle Insurance EDA: Key Insights

1. Demographic Patterns

- Majority of policyholders are **male** and aged **20-40**.
- Older vehicles (**>2 years**) and middle-aged individuals (**41-60**) show higher interest in insurance policies.

2. Insurance Behavior

- Previously **uninsured individuals** are more likely to respond positively to new insurance offers.
- Vehicles with prior **damage history** are associated with higher insurance interest.

3. Policy and Premium Insights

- Annual premiums are concentrated around **₹20,000–40,000**, with claim frequencies peaking for higher premiums (**₹60,000–80,000**).
- No significant trend is observed between **policy vintage** and claim frequency.

4. Regional and Product Strategy

- **Regional variation** in claim frequencies highlights the need for targeted marketing.
- Focus on offering diverse premiums and products for different customer segments, especially for **females** and owners of **older vehicles**.

Conclusion

The analysis underscores the importance of:

- Data-driven marketing strategies.
- Personalized product offerings.
- Targeted customer engagement.

These steps are essential to maximize policyholder retention and acquisition.