Vehicle Insurance EDA

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Objective

The analysis aims to identify key patterns and correlations within the dataset, focusing on customer demographics, insurance behavior, and annual premium trends. Insights highlight outlier impact, customer segmentation by age and gender, regional variations, and factors influencing policy response rates, enabling data-driven strategies for optimizing insurance marketing and pricing.

Step 1: import Necessary Libraries

In [4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Step:2 load the dataset

In [5]:
```
df = pd.read_csv("C:/Users/DELL/Downloads/Vehicle_Insurance.csv")
```

Display the dataset to understand its structure

In [8]:
```
df
```

Out[8]:

	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	Vehicle_Age	Vehicle_Damage	Annual_Premium
0	1	Male	44	1	28.0	0	> 2 Years	Yes	40454.0
1	2	Male	76	1	3.0	0	1-2 Year	No	33536.0
2	3	Male	47	1	28.0	0	> 2 Years	Yes	38294.0
3	4	Male	21	1	11.0	1	< 1 Year	No	28619.0
4	5	Female	29	1	41.0	1	< 1 Year	No	27496.0
...	...	...	...	...	...	...	...	...	...
381104	381105	Male	74	1	26.0	1	1-2 Year	No	30170.0
381105	381106	Male	30	1	37.0	1	< 1 Year	No	40016.0
381106	381107	Male	21	1	30.0	1	< 1 Year	No	35118.0
381107	381108	Female	68	1	14.0	0	> 2 Years	Yes	44617.0
381108	381109	Male	46	1	29.0	0	1-2 Year	No	41777.0

381109 rows × 12 columns

Step 3:Data Overview and initial inspection

1.inspect the first and last few rows:

using df.head() and df.tail() to see a preview.

display the first few rows of the dataset to understand its structure

In [12]:
```
df.head(10)
```

Out[12]:

	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	Vehicle_Age	Vehicle_Damage	Annual_Premium	Policy_Sa
0	1	Male	44	1	28.0	0	> 2 Years	Yes	40454.0	
1	2	Male	76	1	3.0	0	1-2 Year	No	33536.0	
2	3	Male	47	1	28.0	0	> 2 Years	Yes	38294.0	
3	4	Male	21	1	11.0	1	< 1 Year	No	28619.0	
4	5	Female	29	1	41.0	1	< 1 Year	No	27496.0	
5	6	Female	24	1	33.0	0	< 1 Year	Yes	2630.0	
6	7	Male	23	1	11.0	0	< 1 Year	Yes	23367.0	
7	8	Female	56	1	28.0	0	1-2 Year	Yes	32031.0	
8	9	Female	24	1	3.0	1	< 1 Year	No	27619.0	
9	10	Female	32	1	6.0	1	< 1 Year	No	28771.0	

Display the last few rows of the dataset to understand its structure

In [14]:
```
df.tail(10)
```

Out[14]:

	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	Vehicle_Age	Vehicle_Damage	Annual_Premium
381099	381100	Female	51	1	28.0	0	1-2 Year	Yes	44504.0
381100	381101	Female	29	1	28.0	0	< 1 Year	Yes	49007.0
381101	381102	Female	70	1	28.0	0	> 2 Years	Yes	50904.0
381102	381103	Female	25	1	41.0	1	< 1 Year	Yes	2630.0
381103	381104	Male	47	1	50.0	0	1-2 Year	Yes	39831.0
381104	381105	Male	74	1	26.0	1	1-2 Year	No	30170.0
381105	381106	Male	30	1	37.0	1	< 1 Year	No	40016.0
381106	381107	Male	21	1	30.0	1	< 1 Year	No	35118.0
381107	381108	Female	68	1	14.0	0	> 2 Years	Yes	44617.0
381108	381109	Male	46	1	29.0	0	1-2 Year	No	41777.0

2.Understand data types and missing values:

Use df.info() to display column types and check for missing values.

In [16]:
```
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
```

3.Get summary statistics:

Use df.describe() for numerical columns to understand distribution, including mean, median and range.

In [18]:
```
df.describe().T
```

Out[18]:

	count	mean	std	min	25%	50%	75%	max
id	381109.0	190555.000000	110016.836208	1.0	95278.0	190555.0	285832.0	381109.0
Age	381109.0	38.822584	15.511611	20.0	25.0	36.0	49.0	85.0
Driving_License	381109.0	0.997869	0.046110	0.0	1.0	1.0	1.0	1.0
Region_Code	381109.0	26.388807	13.229888	0.0	15.0	28.0	35.0	52.0
Previously_Insured	381109.0	0.458210	0.498251	0.0	0.0	0.0	1.0	1.0
Annual_Premium	381109.0	30564.389581	17213.155057	2630.0	24405.0	31669.0	39400.0	540165.0
Policy_Sales_Channel	381109.0	112.034295	54.203995	1.0	29.0	133.0	152.0	163.0
Vintage	381109.0	154.347397	83.671304	10.0	82.0	154.0	227.0	299.0
Response	381109.0	0.122563	0.327936	0.0	0.0	0.0	0.0	1.0

Step 4: Data Cleaning

1. Handlng missing value

Identify and handle any missing values

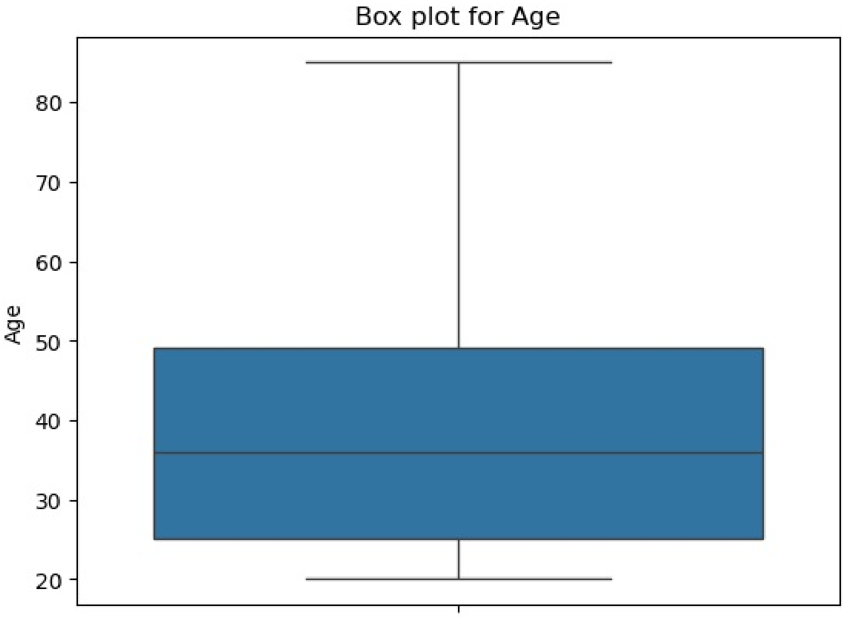
In [20]:
```
df.isnull().sum()
```

Out[20]:
```
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
```

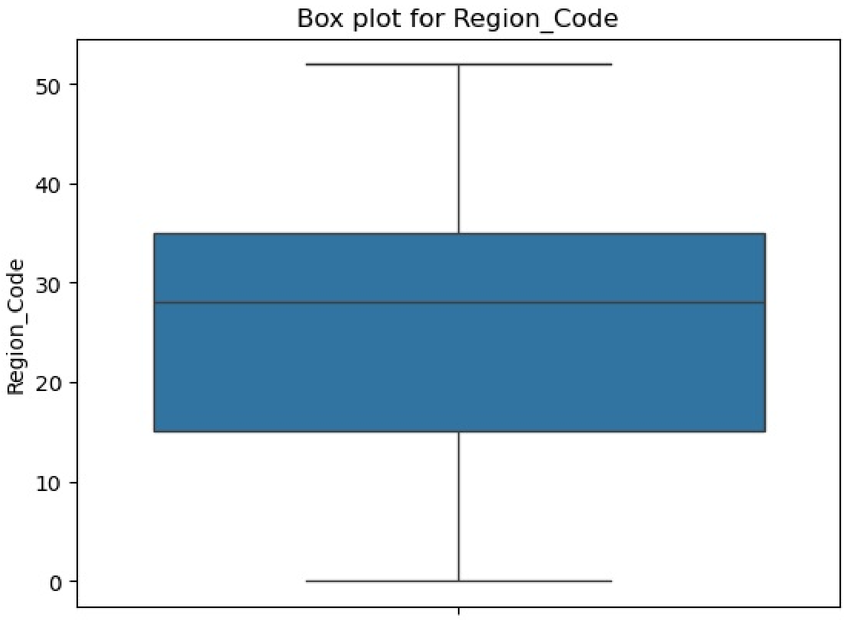
2. Handling Outliers

Identify outliers in numerical columns like Age and Annual_Premium using box plots.

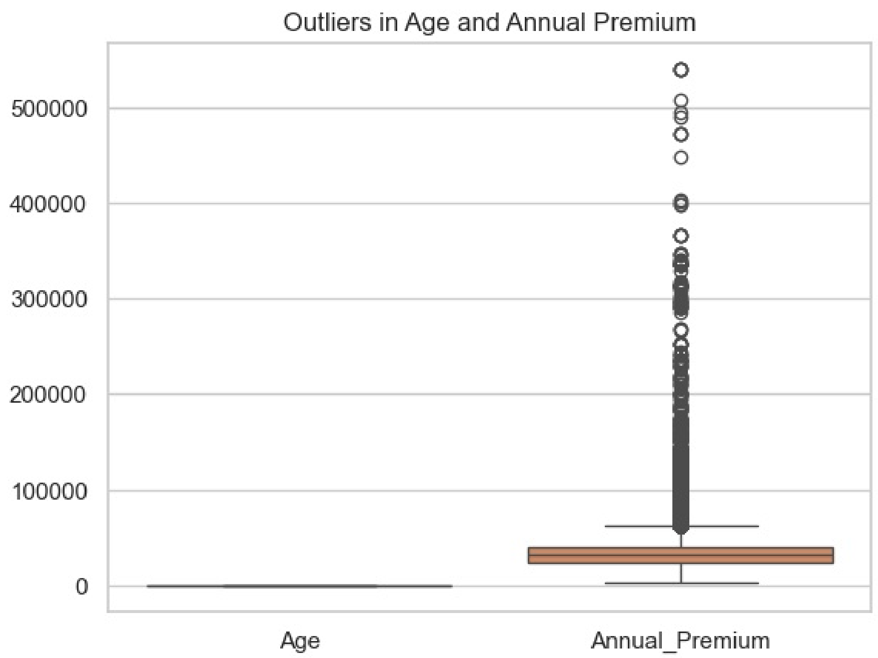
In [22]:
```
sns.boxplot(df['Age'])
plt.title('Box plot for Age')
plt.show()
```



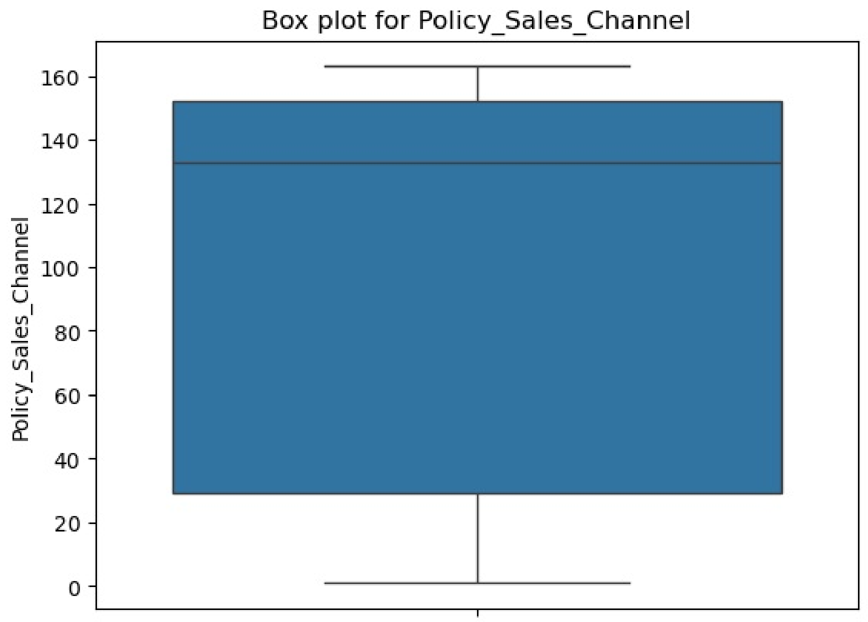
In [24]:
```
sns.boxplot(df['Region_Code'])
plt.title('Box plot for Region_Code')
plt.show()
```



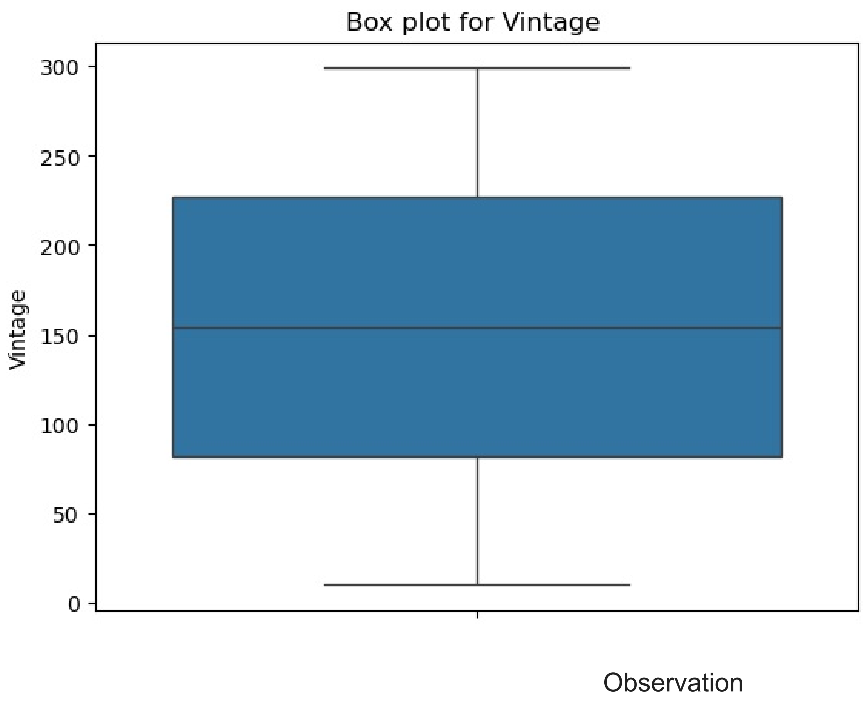
In [381…
```
sns.boxplot(df[['Age','Annual_Premium']])
plt.title("Outliers in Age and Annual Premium")
plt.show()
```




```
In [28]: sns.boxplot(df['Policy_Sales_Channel'])
         plt.title('Box plot for Policy_Sales_Channel')
         plt.show()
```




```
In [30]: sns.boxplot(df['Vintage'])
         plt.title('Box plot for Vintage ')
         plt.show()
```



The Annual Premium column in the dataset contains numerous outliers. These outliers can skew the results and lead to inaccurate predictions in any models built using this data. Therefore, it is essential to address and treat these outliers to ensure the integrity and reliability of any subsequent analysis.

On the other hand, the remaining columns exhibit minimal or no outliers and can be considered stable. Consequently, the primary focus should be on handling the outliers in the Annual Premium column.

In [34]:

```
# calculate the IQR
Q1=df['Annual_Premium'].quantile(0.25)
Q2=df['Annual_Premium'].quantile(0.50)
Q3=df['Annual_Premium'].quantile(0.75)
IQR=Q3-Q1

# define outlier range
lower_bound = Q1 - 1.5*IQR
upper_bound = Q3 + 1.5*IQR

# Identify outliers
outliers = df[(df['Annual_Premium'] < lower_bound) | (df['Annual_Premium'] > upper_bound)]

# Display the calculated values
print(f"Q1: {Q1}")
print(f"Q2: {Q2}")
print(f"Q3: {Q3}")
print(f"IQR: {IQR}")
print(f"lower limit: {lower_bound}")
print(f"upper limit: {upper_bound}")
```

```
Q1: 24405.0
Q2: 31669.0
Q3: 39400.0
IQR: 14995.0
lower limit: 1912.5
upper limit: 61892.5
```

In [36]:

```
outlier_values=df[(df.Annual_Premium <=lower_bound)|(df.Annual_Premium>= upper_bound)]
outlier_values
```

Out[36]:

	id	Gender	Age	Driving_License	Region_Code	Previously_Insured	Vehicle_Age	Vehicle_Damage	Annual_Premium
25	26	Female	21	1	28.0	1	< 1 Year	No	61964.0
37	38	Female	25	1	28.0	1	< 1 Year	No	76251.0
67	68	Male	60	1	28.0	0	1-2 Year	Yes	66338.0
139	140	Male	21	1	29.0	1	< 1 Year	No	62164.0
149	150	Female	22	1	11.0	1	< 1 Year	No	76651.0
...	...	...	...	...	...	...	...	...	...
380959	380960	Male	25	1	8.0	1	< 1 Year	No	61909.0
380998	380999	Female	33	1	8.0	0	1-2 Year	Yes	101664.0
381035	381036	Female	22	1	11.0	1	< 1 Year	No	62889.0
381047	381048	Female	52	1	8.0	1	1-2 Year	No	71915.0
381079	381080	Male	33	1	28.0	0	< 1 Year	Yes	69845.0

10320 rows × 12 columns

Replacing Outliers With Median Value

In [39]:

```
meanv=df[(df['Annual_Premium']>lower_bound)&(df['Annual_Premium']<upper_bound)]['Annual_Premium'].median()
meanv
```

Out[39]:

```
31319.0
```

In [45]:

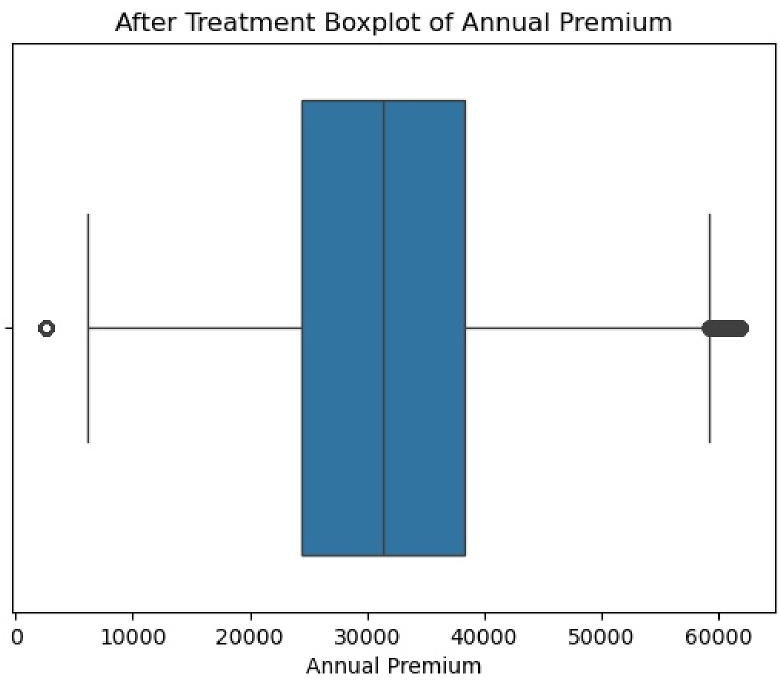
```
df['Annual_Premium'] = np.where((df['Annual_Premium'] < lower_bound) | (df['Annual_Premium'] > upper_bound), mea
df['Annual_Premium'].head(28)
```

Out[45]:

```
0     40454.0
1     33536.0
2     38294.0
3     28619.0
4     27496.0
5      2630.0
6     23367.0
7     32031.0
8     27619.0
9     28771.0
10    47576.0
11    48699.0
12    31409.0
13    36770.0
14    46818.0
15     2630.0
16    26218.0
17    46622.0
18    33667.0
19    32363.0
20    41184.0
21    50791.0
22    45283.0
23    41852.0
24    38111.0
25    31319.0
26    38341.0
27    19135.0
Name: Annual_Premium, dtype: float64
```

In [47]:

```
sns.boxplot(x=df['Annual_Premium'])
plt.xlabel('Annual Premium')
plt.title('After Treatment Boxplot of Annual Premium')
plt.show()
```

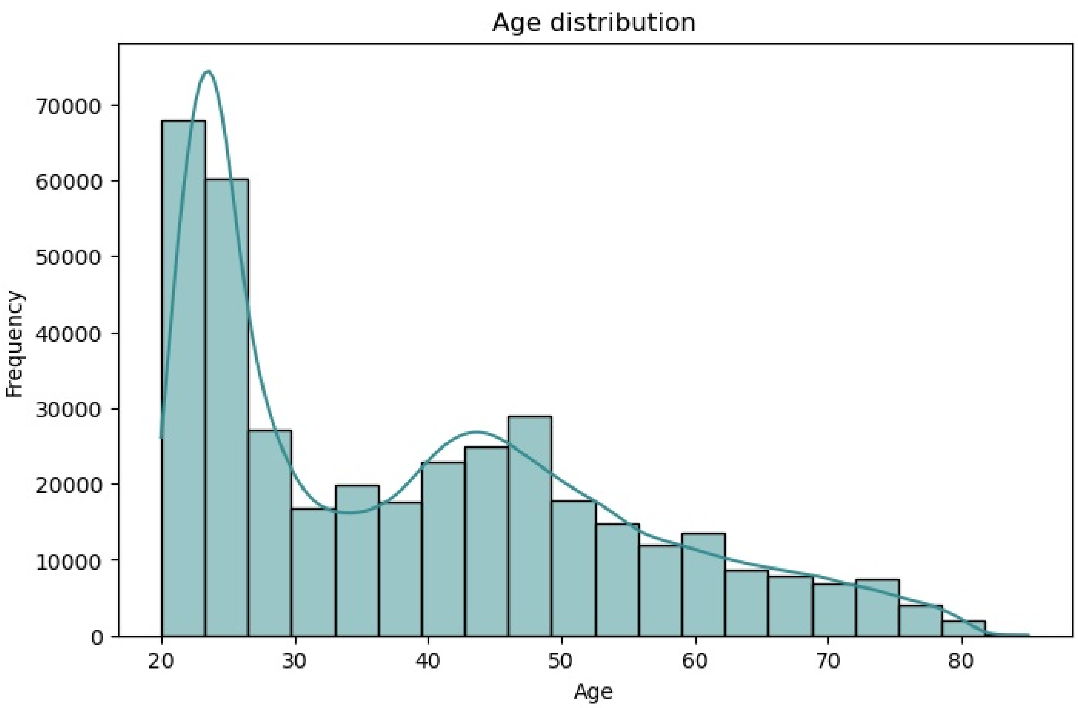


Step 5: Data Visualization

1. Age Distribution

Visualize the distribution of Age to understand the age demographics of customers.

In [99]:
```
plt.figure(figsize=(8,5))
sns.histplot(df['Age'],bins=20,kde=True,color="#378E92")
plt.title("Age distribution")
plt.xlabel("Age")
plt.ylabel("Frequency")
plt.show()
```



Observations:

The histogram shows the distribution of ages within the dataset. The distribution is right-skewed, with a peak around the age of 25-30. This indicates a higher proportion of younger individuals in the dataset. The tail extending towards older ages suggests a smaller but still significant number of older individuals.

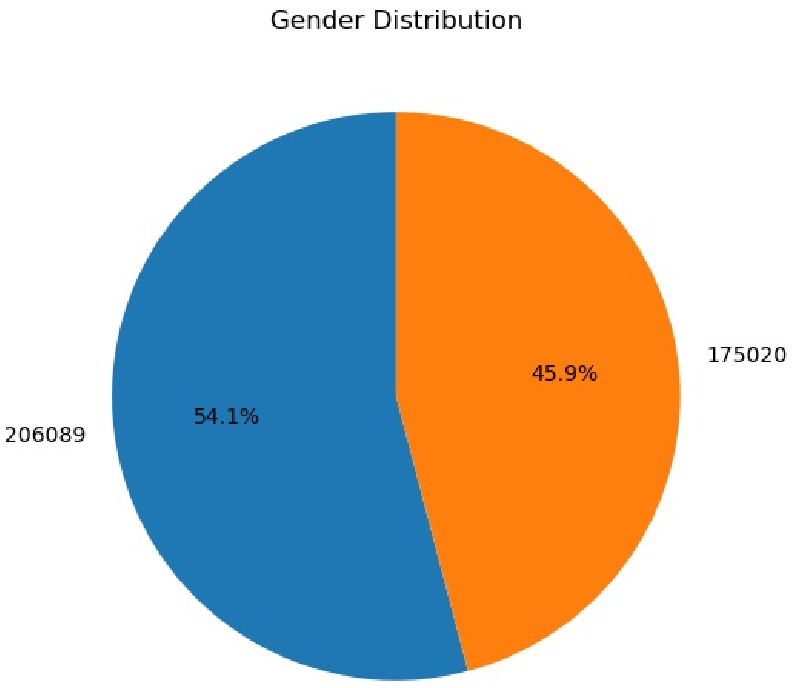
Recommendations:

The age distribution chart shows a right-skewed distribution, indicating a higher concentration of younger individuals. To drive growth in vehicle insurance, focus on targeting the younger demographic with tailored insurance products and marketing strategies. Additionally, consider expanding product offerings to cater to the specific needs of older customers, such as specialized insurance for senior citizens.

2. Gender Distribution

Visualize the gender distribution to see if there is any imbalance.

In [101…
```
gender_counts=df['Gender'].value_counts()
plt.figure(figsize=(6,6))
plt.pie(gender_counts,labels=gender_counts,autopct='%1.1f%%',startangle=90)
plt.title('Gender Distribution')
plt.show()
```



Observations:

The gender distribution chart reveals that males constitute a larger portion of the customer base, accounting for 54.1% compared to 45.9% for females. This suggests that male drivers are more likely to opt for vehicle insurance policies.

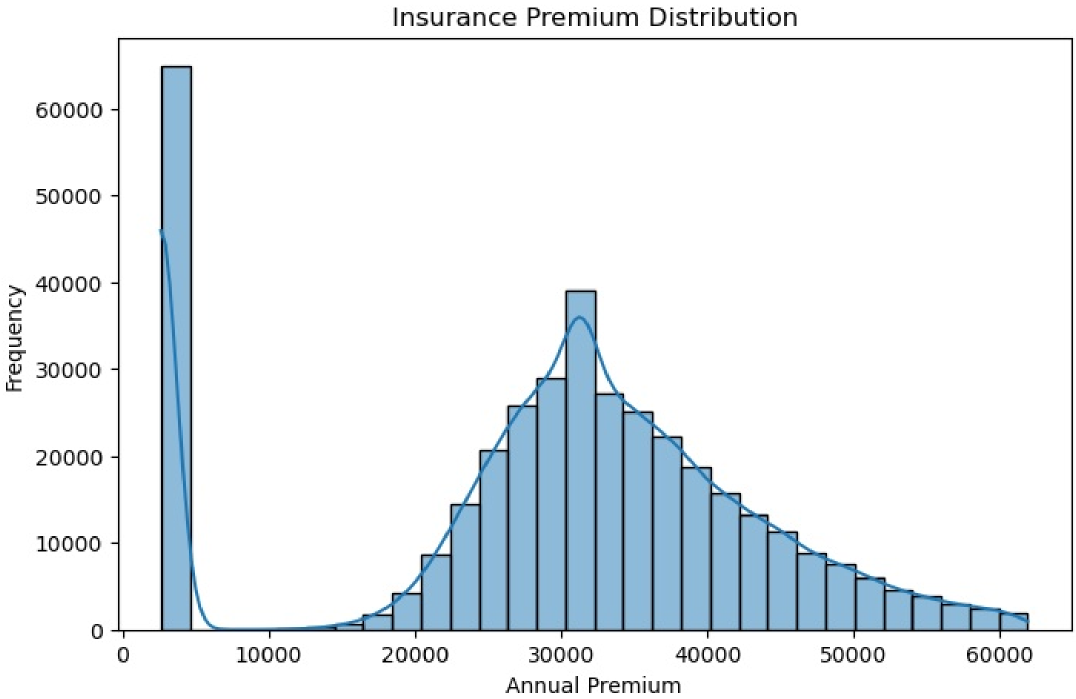
Recommendations:

The gender distribution chart reveals a slight male dominance in the dataset. To drive growth, consider targeted marketing campaigns that address the specific needs and preferences of both genders

3. Premium Analysis

Examine the distribution of Annual Premium to understand common premium values.

In [103…
```
plt.figure(figsize=(8,5))
sns.histplot(df['Annual_Premium'],bins=30,kde=True)
plt.title("Insurance Premium Distribution")
plt.xlabel("Annual Premium")
plt.ylabel("Frequency")
plt.show()
```



Observations:

The insurance premium distribution chart shows a right-skewed distribution, indicating that most policies have lower annual premiums, with a smaller proportion of policies having significantly higher premiums. This could be due to factors like vehicle type, model, age, and driver profile.

Recommendations:

Targeted Marketing: Implement targeted marketing campaigns to attract customers in the lower premium range who might be price-sensitive. Offer competitive pricing and value-added services to attract this segment.

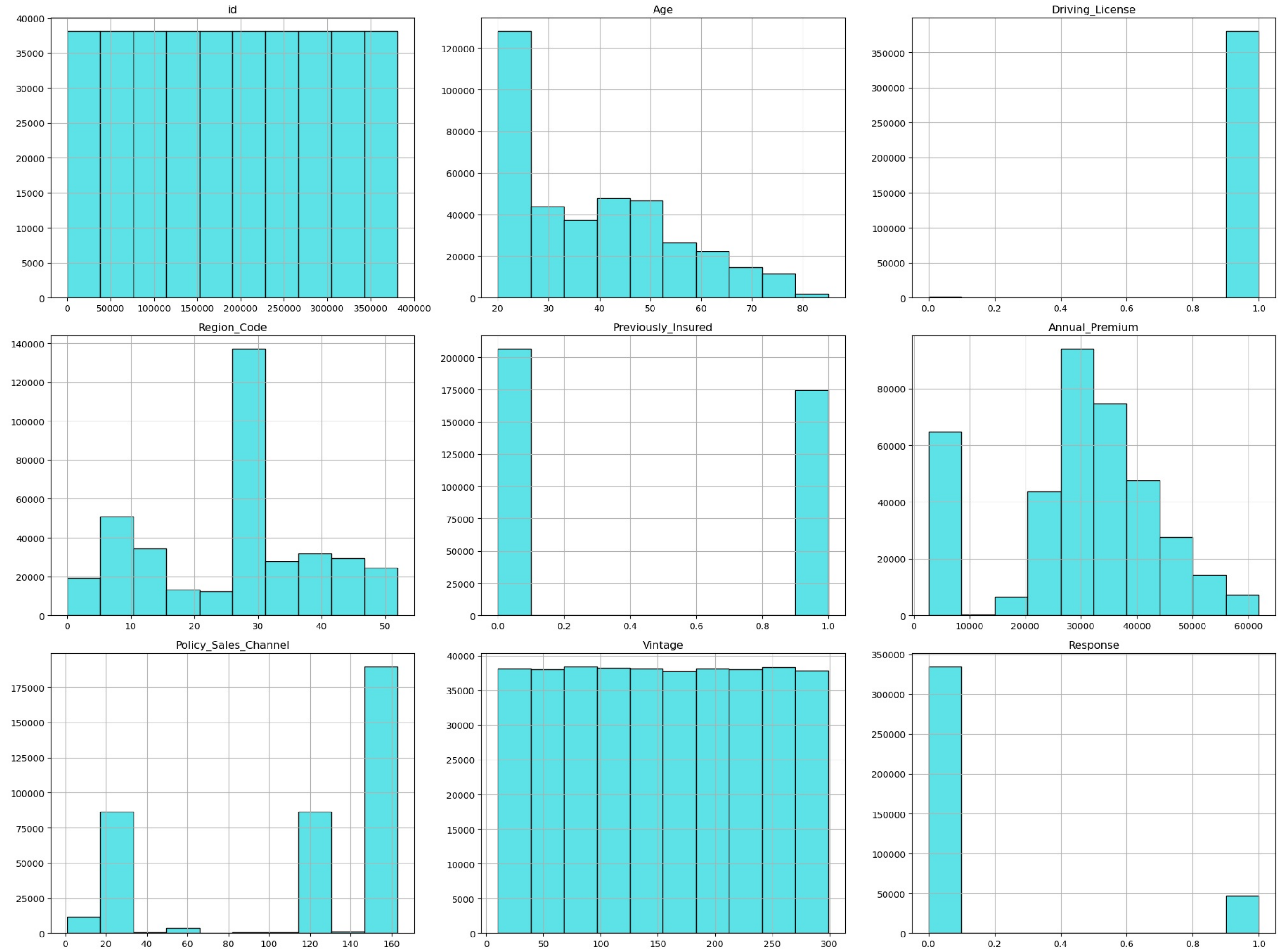
Product Bundling: Consider creating product bundles that combine basic insurance coverage with additional services like roadside assistance or accident repair services at discounted rates.

Risk Segmentation: Analyze the data to identify specific risk factors associated with higher premiums. Implement risk-based pricing strategies to offer customized policies that cater to different risk profiles.

Customer Education: Educate customers about the importance of adequate insurance coverage and the factors that influence premium costs. This can help them make informed decisions and choose the right coverage for their needs.

In [105…

```
df.hist(figsize=(20,15),color='#5DE2E7',edgecolor='black')
plt.gcf().set_facecolor('white')
plt.tight_layout()
plt.show()
```



Observations and Recommendations from the Charts

1. Region Code

Observation: The distribution appears uneven, suggesting varying levels of activity across different regions.

Recommendation: Analyze the performance of each region and identify areas with high potential for growth. Focus on targeted marketing and promotional strategies for regions with lower penetration.

2. Age

Observation: The distribution is right-skewed, indicating a larger proportion of younger customers.

Recommendation: Leverage this demographic advantage by offering tailored insurance products and marketing campaigns that appeal to younger customers. Consider discounts for safe driving and good academic records.

3. Driving License

Observation: The distribution is heavily skewed towards one category, suggesting a high percentage of customers with valid driving licenses.

Recommendation: Focus on customer retention strategies to ensure long-term loyalty. Offer value-added services and loyalty programs to retain existing customers.

4. Annual Premium

Observation: The distribution is right-skewed, indicating a higher number of customers with lower annual premiums.

Recommendation: Implement targeted marketing campaigns to upsell higher-premium products to existing customers. Offer flexible payment options and bundling discounts to encourage higher premium purchases.

5. Region Code

Observation: Similar to the first chart, the distribution is uneven, suggesting varying levels of activity across different regions.

6. Previously Insured

Observation: The distribution is skewed towards one category, indicating a high percentage of customers who were previously insured.

Recommendation: Leverage this existing customer base by offering seamless renewal processes and personalized recommendations for additional coverage.

7. Vintage

Observation: The distribution is relatively even, indicating a balanced customer base across different policy durations.

Recommendation: Implement retention strategies to increase policy tenure and reduce churn. Offer incentives for long-term policyholders, such as discounts on renewals or additional benefits.

8. Policy Sales Channel

Observation: The distribution is uneven, indicating varying levels of activity across different sales channels.

Recommendation: Analyze the performance of each sales channel and identify opportunities for optimization. Focus on channels with higher conversion rates and lower acquisition costs.

9. Response

Observation: The distribution is skewed towards one category, indicating a high percentage of customers who responded to marketing campaigns.

Recommendation: Continue to refine marketing strategies to improve response rates. Use data-driven insights to personalize marketing messages and optimize campaign timing.

In [ ]:

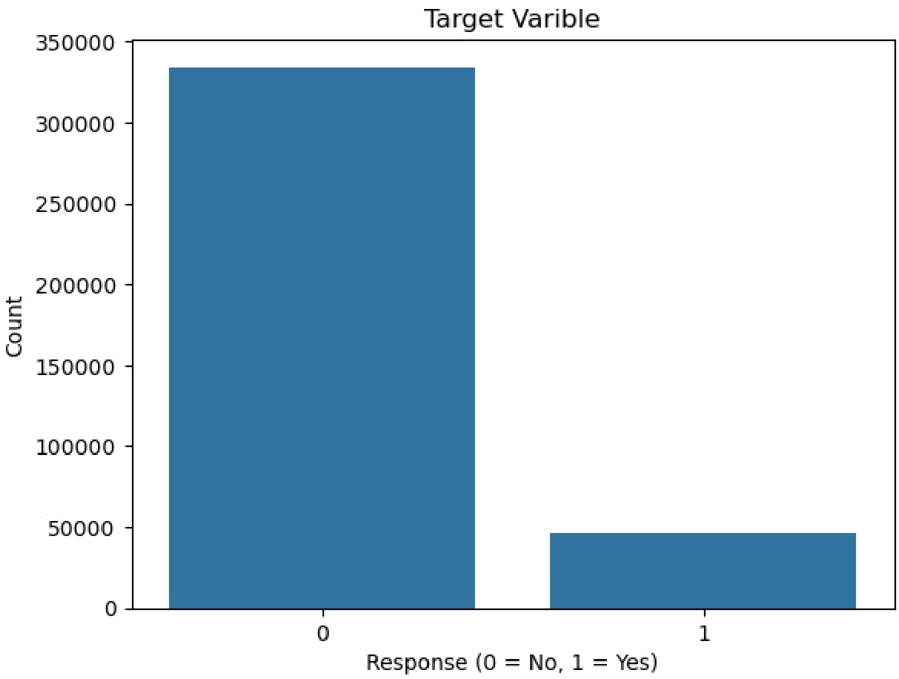
Step 6: Feature Analysis and Relationships

1.Target Variable (Response)

Visualize the distribution of the Response Variables, Which indicates if a customer made an insurance claim.

In [107…

```
sns.countplot(data=df,x='Response')
plt.title("Target Varible")
plt.xlabel("Response (0 = No, 1 = Yes)")
plt.ylabel("Count")
plt.show()
```



Observations:

The target variable distribution shows a significant class imbalance, with a much higher proportion of instances belonging to the negative class (0). This indicates a potential challenge in building accurate predictive models, as the model may be biased towards the majority class.

Recommendations:

Data Balancing: Employ techniques like oversampling the minority class or undersampling the majority class to create a more balanced dataset. This can help improve model performance and reduce bias.

Evaluation Metrics: Use appropriate evaluation metrics that are robust to class imbalance, such as F1-score, precision, recall, or ROC-AUC. These metrics provide a more comprehensive assessment of model performance.

Display counts for each response type

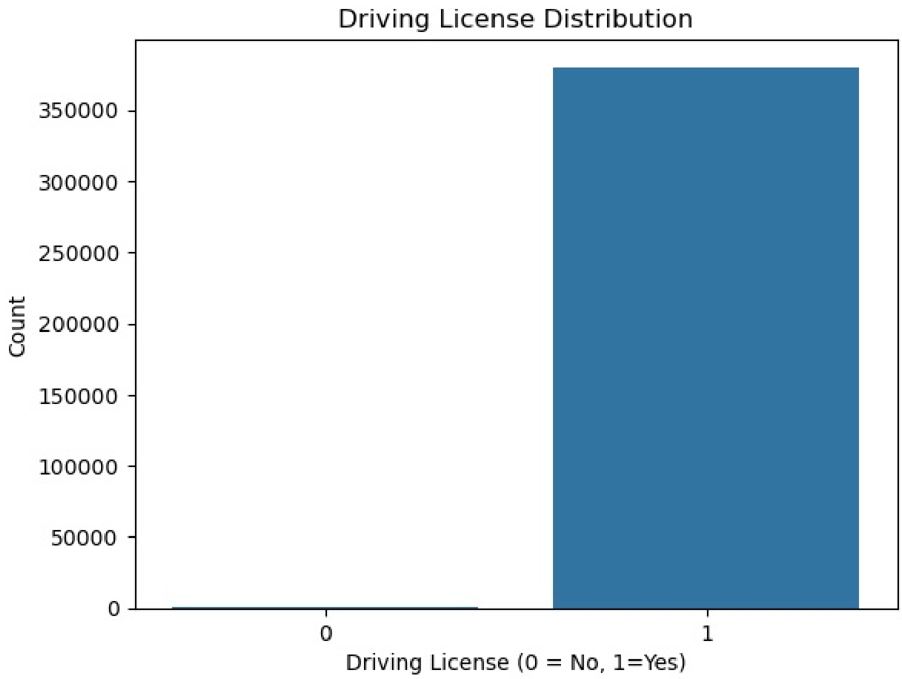
In [109…
```
df.Response.value_counts()
```

Out[109…
```
Response
0    334399
1     46710
Name: count, dtype: int64
```

2. Driving License Distribution

Check the distribution of Driving License holders in the dataset.

In [111…
```
sns.countplot(data=df,x='Driving_License')
plt.title("Driving License Distribution")
plt.xlabel("Driving License (0 = No, 1=Yes)")
plt.ylabel("Count")
plt.show()
```



Observations:

The driving license distribution chart shows a significant imbalance, with a vast majority of customers having a driving license. This indicates that the presence of a driving license is a strong predictor of vehicle insurance eligibility.

Recommendations:

Targeted Marketing: Focus on individuals who do not have a driving license but may be potential customers for other insurance products like health or home insurance.

Product Bundling: Create bundled insurance packages that include vehicle insurance along with other relevant products, such as health insurance or travel insurance, to attract a wider customer base.

Display counts for each driving license

In [113…
```
df.Driving_License.value_counts()
```

Out[113…
```
Driving_License
1    380297
0       812
Name: count, dtype: int64
```

3. Distribution of Previously insured

Display counts for each previosly insurance

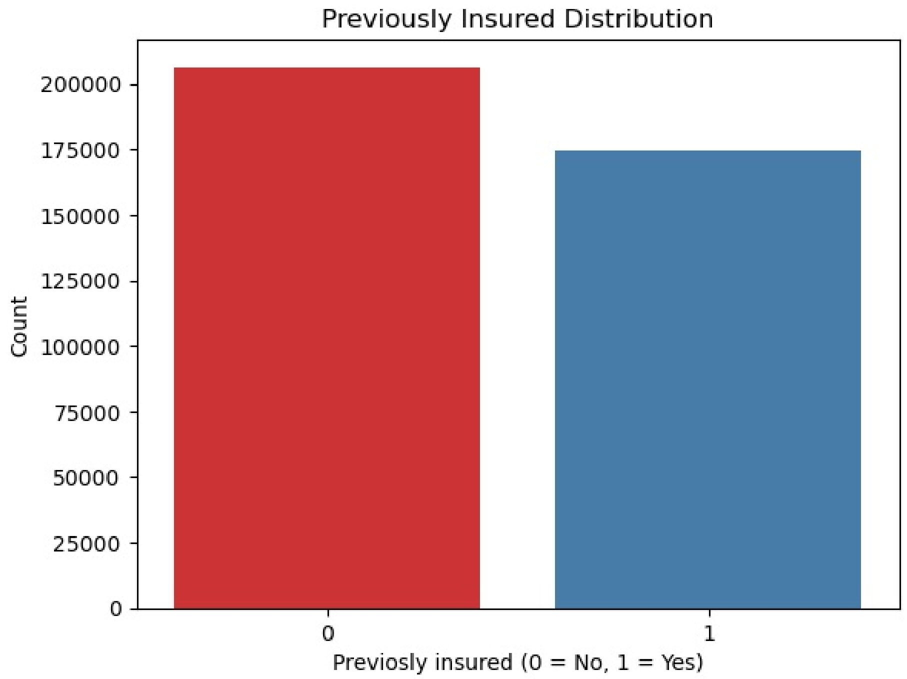
In [115…
```
df.Previously_Insured.value_counts()
```

Out[115…
```
Previously_Insured
0    206481
1    174628
Name: count, dtype: int64
```

Analyze the Previously Insured feature to see the proportion of insured and uninsured customers.

In [117…
```
sns.countplot(data=df,x='Previously_Insured',palette='Set1')
plt.title("Previosly Insured Distribution")
plt.xlabel("Previosly insured (0 = No, 1 = Yes)")
plt.ylabel("Count")
plt.show()
```

```
C:\Users\DELL\AppData\Local\Temp\ipykernel_1564\2947124128.py:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(data=df,x='Previously_Insured',palette='Set1')
```



Observations:

The "Previously Insured" distribution shows a significant imbalance, with a larger proportion of customers having prior insurance experience. This indicates that past insurance experience could be a strong predictor of future insurance behavior.

Recommendations:

Retention Strategies: Focus on retaining existing customers by offering competitive renewal rates, loyalty programs, and personalized services.

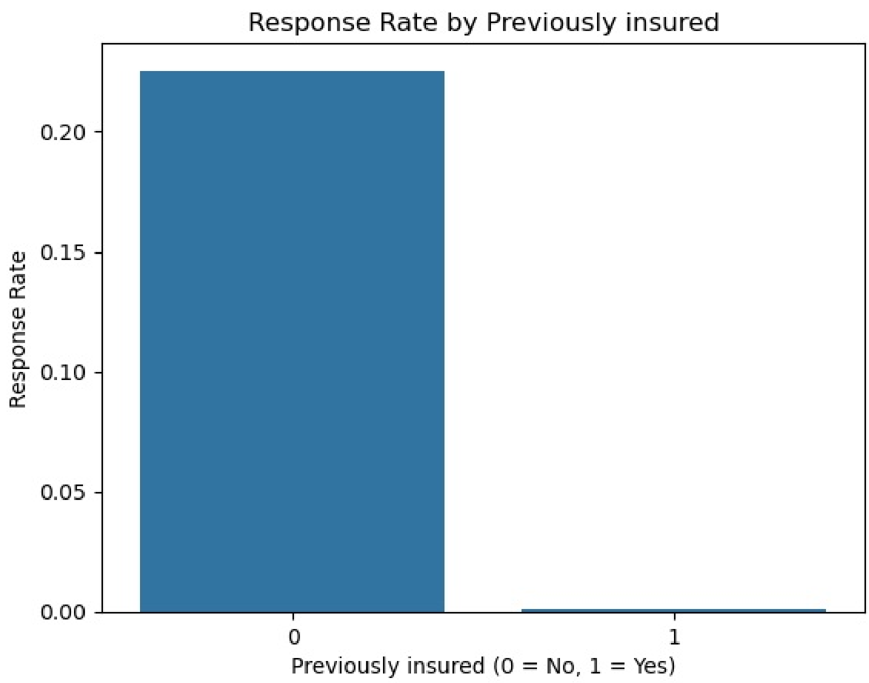
Cross-Selling: Leverage the existing customer base to cross-sell additional insurance products, such as health insurance or home insurance.

Targeted Marketing: Target individuals with prior insurance experience through personalized marketing campaigns that highlight the benefits of switching to your insurance provider.

4. Response Rate by Previously Insured

Explore the average claim response rate based on whether the customer was previously insured.

In [119…
```
insured_response = df.groupby('Previously_Insured')['Response'].mean().reset_index()
sns.barplot(x='Previously_Insured',y='Response',data=insured_response)
plt.title("Response Rate by Previously insured")
plt.xlabel("Previously insured (0 = No, 1 = Yes)")
plt.ylabel("Response Rate")
plt.show()
```



Observations:

The chart shows a significant difference in response rates between previously insured and non-insured customers. Customers with prior insurance experience are significantly less likely to respond to marketing campaigns compared to those who have not been previously insured.

Recommendations:

Targeted Marketing: Focus on tailoring marketing campaigns to the specific needs and preferences of previously insured customers. Offer personalized incentives and highlight the unique benefits of switching to your insurance provider.

Customer Relationship Management: Prioritize building strong relationships with previously insured customers through effective communication, prompt claims processing, and proactive customer service.

Data-Driven Marketing: Utilize data analytics to identify high-value customers and tailor marketing efforts accordingly. This can help optimize marketing spend and improve response rates.

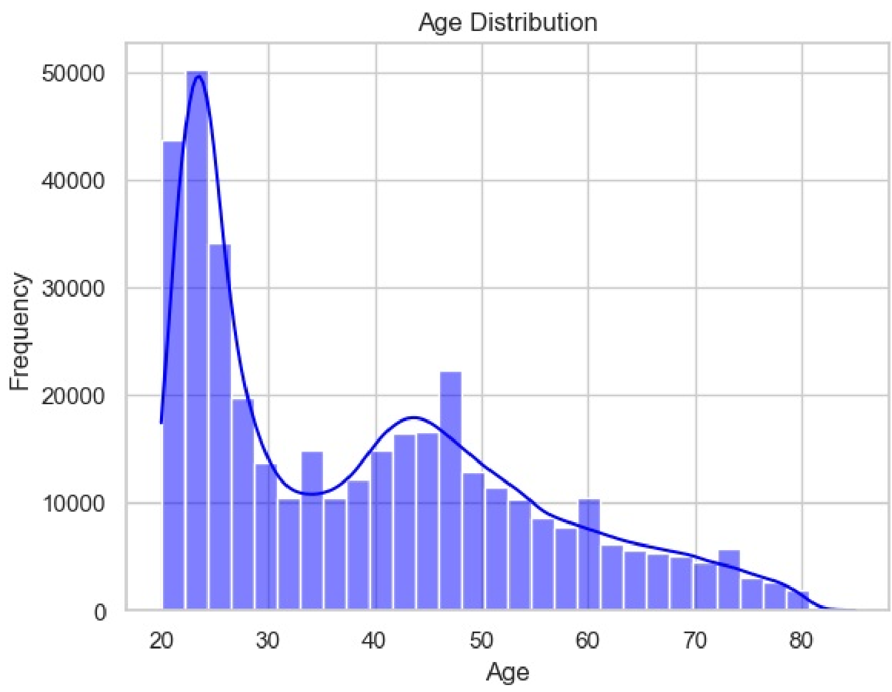
Step 7: Age Distribution:

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

Age Distribution By customers

In [122…

```
sns.set(style="whitegrid")
sns.histplot(df['Age'],bins=30,kde=True,color='blue')
plt.title("Age Distribution")
plt.xlabel("Age")
plt.ylabel("Frequency")
plt.show()
```



Observations:

The age distribution is right-skewed, indicating a larger proportion of younger customers. This suggests a potentially higher risk profile due to less driving experience and higher accident rates among younger drivers.

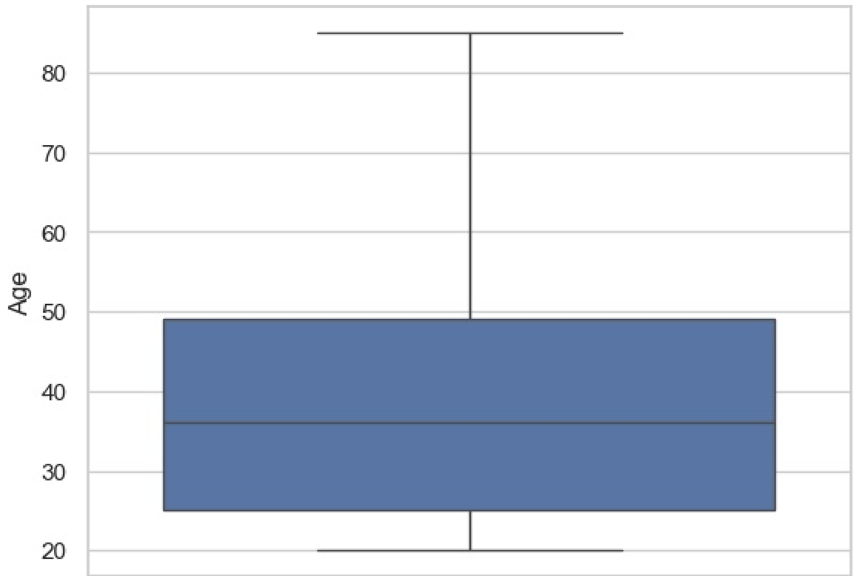
Recommendations:

Risk-Based Pricing: Implement a risk-based pricing strategy that considers factors like age and driving experience to accurately assess risk and set appropriate premiums.

Targeted Marketing: Develop targeted marketing campaigns to attract and retain younger customers, emphasizing the importance of insurance coverage and offering discounts or incentives for safe driving.

In [126…

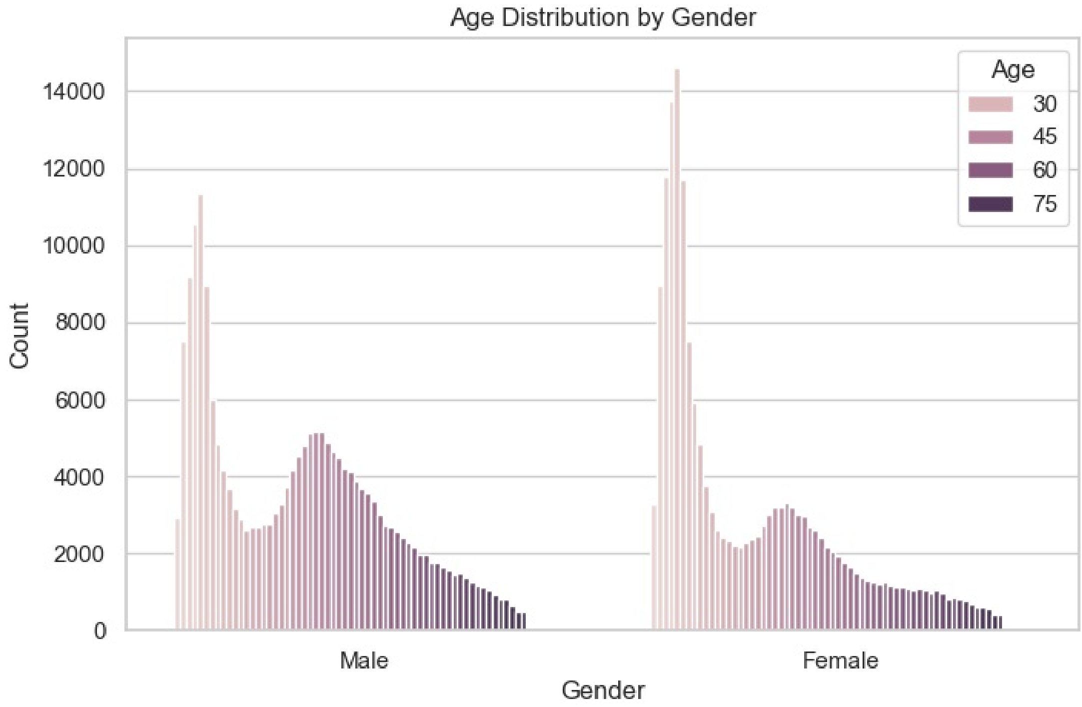
```
sns.boxplot(y='Age',data=df)
plt.show()
```



Age Distribution by Gender

In [159…

```
plt.figure(figsize=(8, 5))
sns.countplot(x='Gender', hue='Age', data=df)
plt.title('Age Distribution by Gender')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()
```



Observations:

The age distribution by gender shows a similar pattern for both males and females, with a peak around the age of 30 and a gradual decline thereafter. However, there seems to be a slightly higher proportion of younger females compared to younger males.

Recommendations:

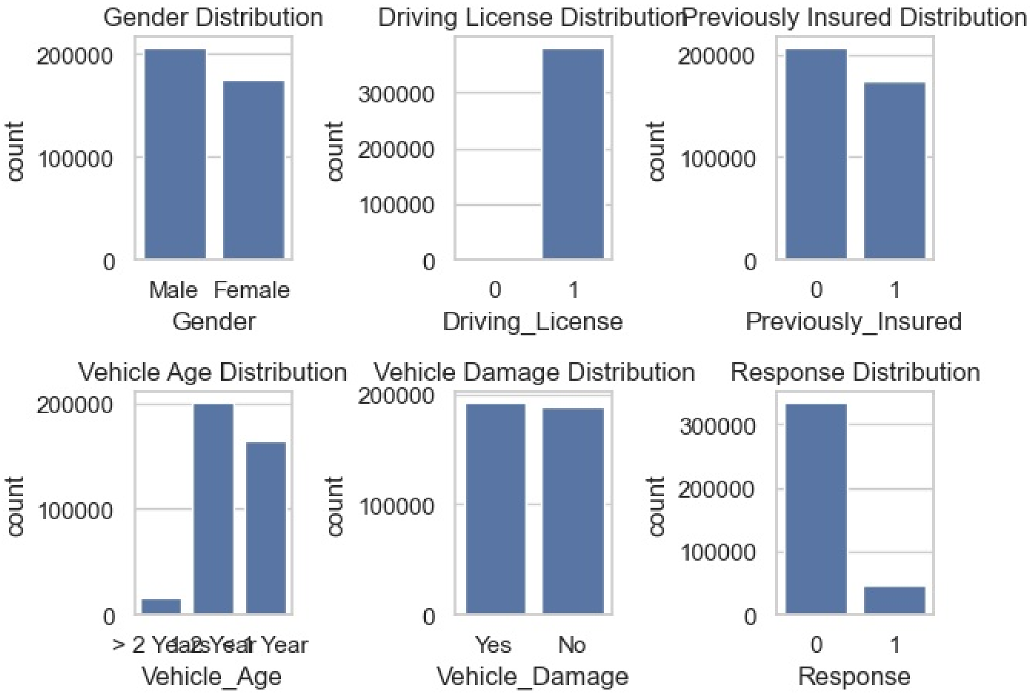
Targeted Marketing: Implement targeted marketing campaigns for younger females, highlighting the importance of insurance coverage and offering special discounts or incentives for this demographic.

Risk-Based Pricing: Consider adjusting pricing strategies to reflect the different risk profiles associated with different age groups and genders.

Product Customization: Develop customized insurance products that cater to the specific needs and preferences of different age groups, such as additional coverage for young drivers or senior citizens.

In [130…

```
plt.subplot(2,3,1)
sns.countplot(x='Gender',data=df)
plt.title("Gender Distribution")

plt.subplot(2,3,2)
sns.countplot(x='Driving_License',data=df)
plt.title("Driving License Distribution")

plt.subplot(2,3,3)
sns.countplot(x='Previously_Insured',data=df)
plt.title("Previously Insured Distribution")

plt.subplot(2,3,4)
sns.countplot(x='Vehicle_Age',data=df)
plt.title("Vehicle Age Distribution")

plt.subplot(2,3,5)
sns.countplot(x='Vehicle_Damage',data=df)
plt.title("Vehicle Damage Distribution")

plt.subplot(2,3,6)
sns.countplot(x='Response',data=df)
plt.title("Response Distribution")

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



Observations and Recommendations

Gender Distribution:

Observation: The distribution is relatively balanced between male and female customers.

Recommendation: Implement gender-neutral marketing strategies to appeal to both genders.

Driving License Distribution:

Observation: The majority of customers have a valid driving license.

Recommendation: Leverage this information to target customers with personalized offers and incentives.

Previously Insured Distribution:

Observation: A significant proportion of customers have prior insurance experience.

Recommendation: Focus on retention strategies to retain existing customers and offer them attractive renewal options.

Vehicle Age Distribution:

Observation: The distribution is skewed towards newer vehicles.

Recommendation: Target customers with older vehicles and offer them special discounts or incentives to upgrade their insurance policies.

Vehicle Damage Distribution:

Observation: The majority of vehicles have not been damaged.

Recommendation: Implement telematics programs to track driver behavior and offer discounts for safe driving.

Response Distribution:

Observation: The majority of customers have not responded to marketing campaigns.

Recommendation: Refine marketing strategies to improve response rates, such as personalized messaging and targeted offers.

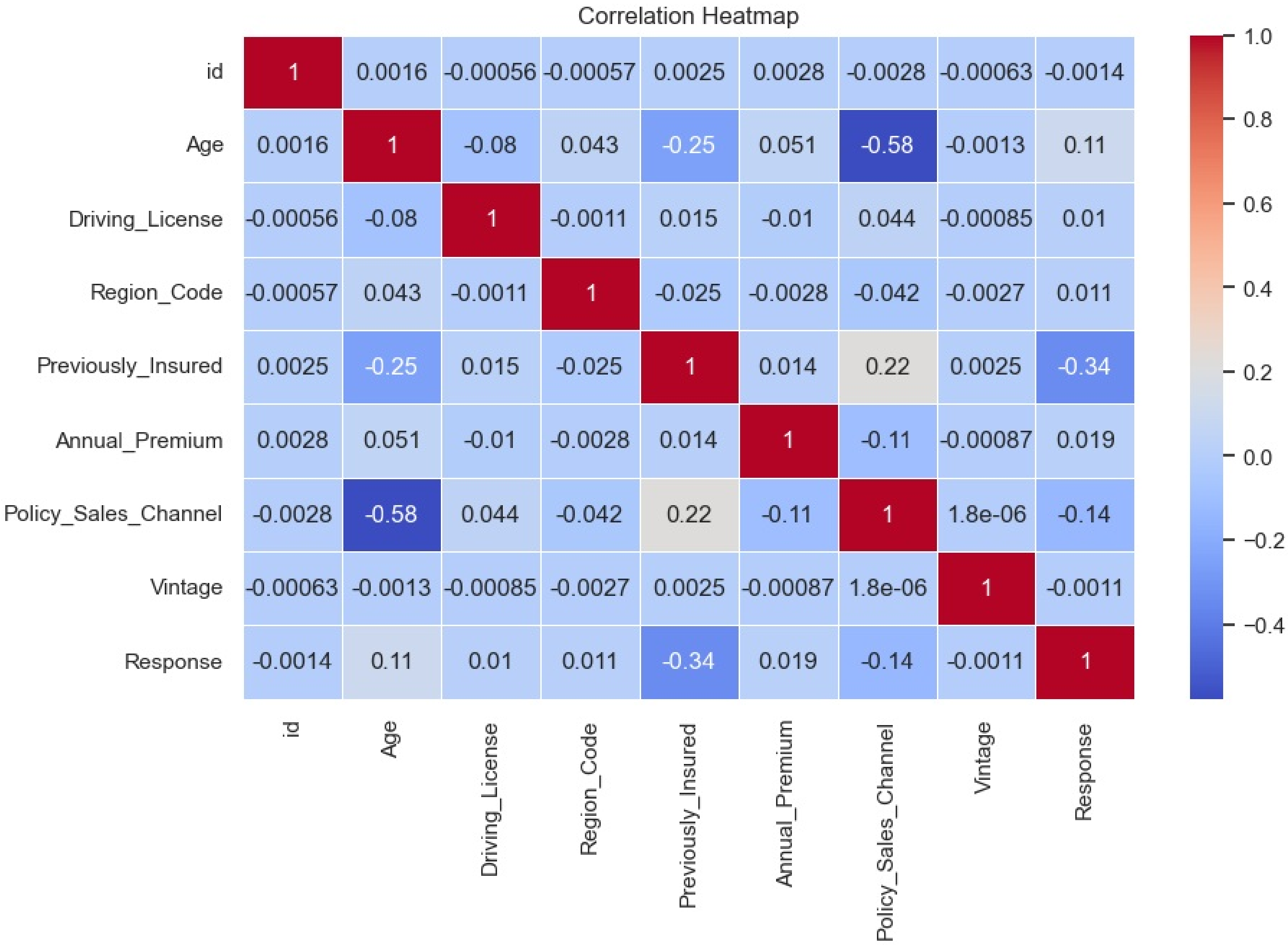
Step 8: Premium Analysis:

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

In [132…

```
# Assuming df is your DataFrame
df1 = pd.DataFrame(df)

# Select only numeric columns
```

```python
numeric_df = df1.select_dtypes(include='number')

# Calculate correlation
correlation_matrix = numeric_df.corr()

# Plot heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title("Correlation Heatmap")
plt.show()
```



Observations:

Age and Response: There is a positive correlation between age and response rate. This suggests that older customers are more likely to respond to marketing campaigns.

Policy Sales Channel and Response: There is a negative correlation between the policy sales channel and response rate. This indicates that certain sales channels may be less effective in generating responses.

Previously Insured and Response: There is a negative correlation between previously insured customers and response rate. This suggests that customers who have been previously insured are less likely to respond to marketing campaigns.

Recommendations:

Age-Based Targeting: Tailor marketing campaigns to different age groups, focusing on personalized messaging and incentives that resonate with each segment.

Channel Optimization: Analyze the performance of different sales channels and focus on those with higher response rates. Consider optimizing marketing efforts for these channels to improve customer engagement.

Retention Strategies: Implement effective retention strategies to maintain relationships with previously insured customers. Offer personalized renewal offers and incentives to encourage continued business.

Data-Driven Marketing: Utilize data analytics to identify high-value customers and tailor marketing efforts accordingly. This can help optimize marketing spend and improve response rates.

Step 9: Gender Analysis:

Driving License by Gender

Explore the relationship between Gender and Driving License Status.

In [134…

```
df2=df.groupby(['Gender'])['Driving_License'].count().to_frame().reset_index()
df2
```

Out[134…

	Gender	Driving_License
0	Female	175020
1	Male	206089

In [136…

```
sns.barplot(x="Gender", y="Driving_License",data=df2)
plt.title("Driving License By Gender")
plt.xlabel("Gender")
plt.ylabel("Driving License")
plt.show()
```

Observations:

The chart shows a higher number of male customers with driving licenses compared to female customers. This suggests a potential market opportunity for targeting female customers.

Recommendations:

Targeted Marketing: Implement targeted marketing campaigns for female customers, highlighting the importance of insurance coverage and offering special discounts or incentives for women drivers.

Product Customization: Develop customized insurance products that cater to the specific needs and preferences of female customers, such as additional coverage for safety features or discounts for safe driving.

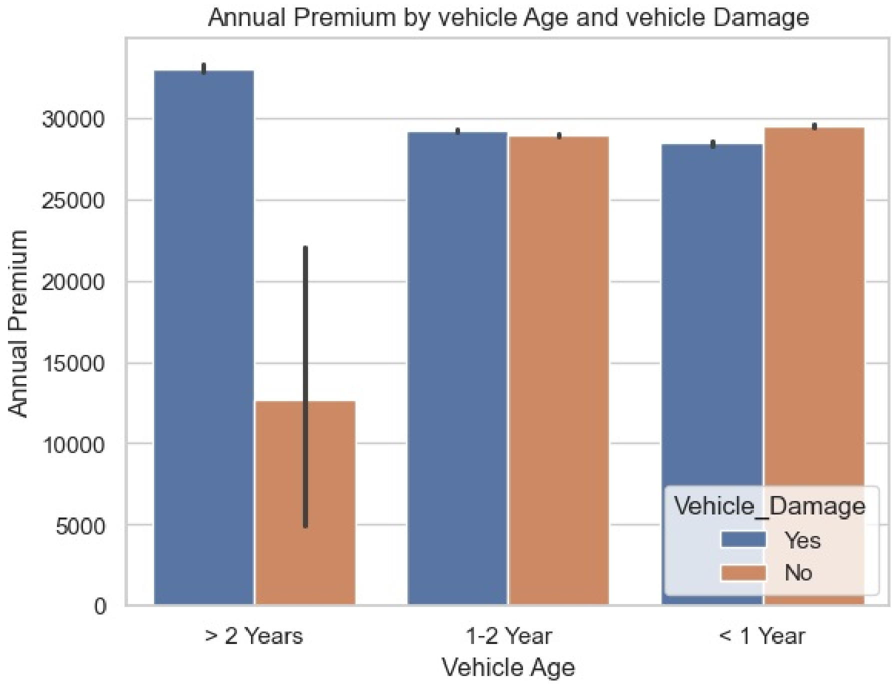
Partnership with Women's Organizations: Collaborate with women's organizations to promote the importance of insurance and offer exclusive discounts or benefits to their members.

Step 10: Vehicle Age and Claims:

Examine the impact of vehicle age on insuance claims.

In [139…

```
sns.barplot(data=df,x='Vehicle_Age',y='Annual_Premium',hue='Vehicle_Damage')
plt.title("Annual Premium by vehicle Age and vehicle Damage")
plt.xlabel("Vehicle Age")
plt.ylabel("Annual Premium")
plt.show()
```



Observations:

The chart shows that vehicles with damage have significantly higher annual premiums compared to those without damage.

Additionally, the annual premium increases as the vehicle age decreases.

Recommendations:

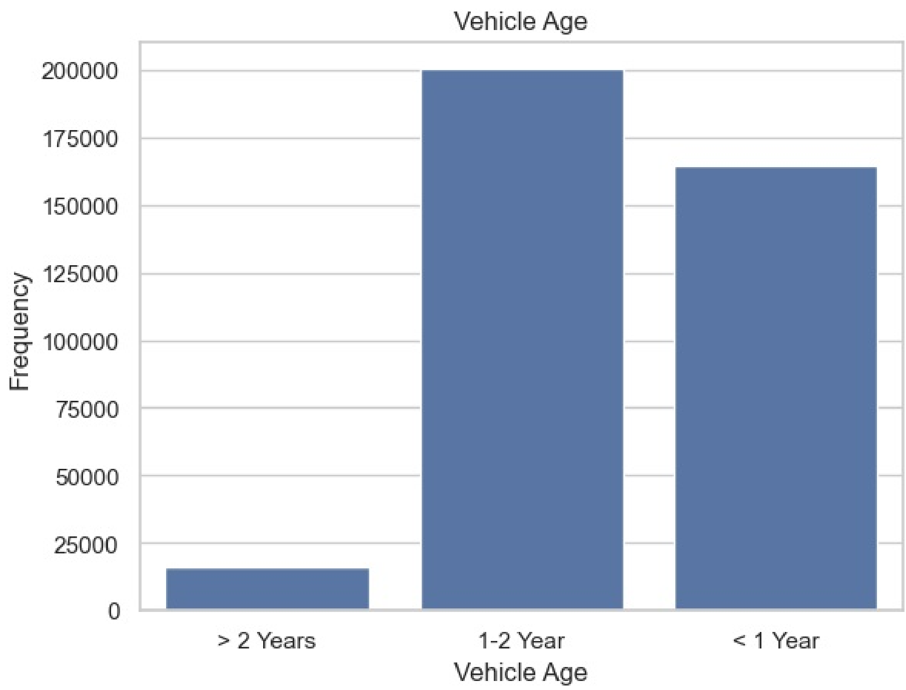
Risk-Based Pricing: Implement a risk-based pricing model that accurately reflects the risk associated with different vehicle ages and damage histories.

Telematics Programs: Consider using telematics devices to monitor driver behavior and offer discounts to safe drivers, regardless of vehicle age or damage history.

Customer Education: Educate customers about the factors that influence insurance premiums and how they can mitigate risk to lower their costs.

In [140…

```
sns.countplot(data=df,x='Vehicle_Age')
plt.title("Vehicle Age")
plt.xlabel("Vehicle Age")
plt.ylabel("Frequency")
plt.show()
```



Observations:

The majority of vehicles in the dataset are less than a year old, followed by vehicles between 1 and 2 years old. Vehicles older than 2 years represent the smallest proportion.

Recommendations:

Targeted Marketing: Focus on targeting customers with newer vehicles, as they represent a significant portion of the market. Offer competitive pricing and value-added services to attract and retain these customers.

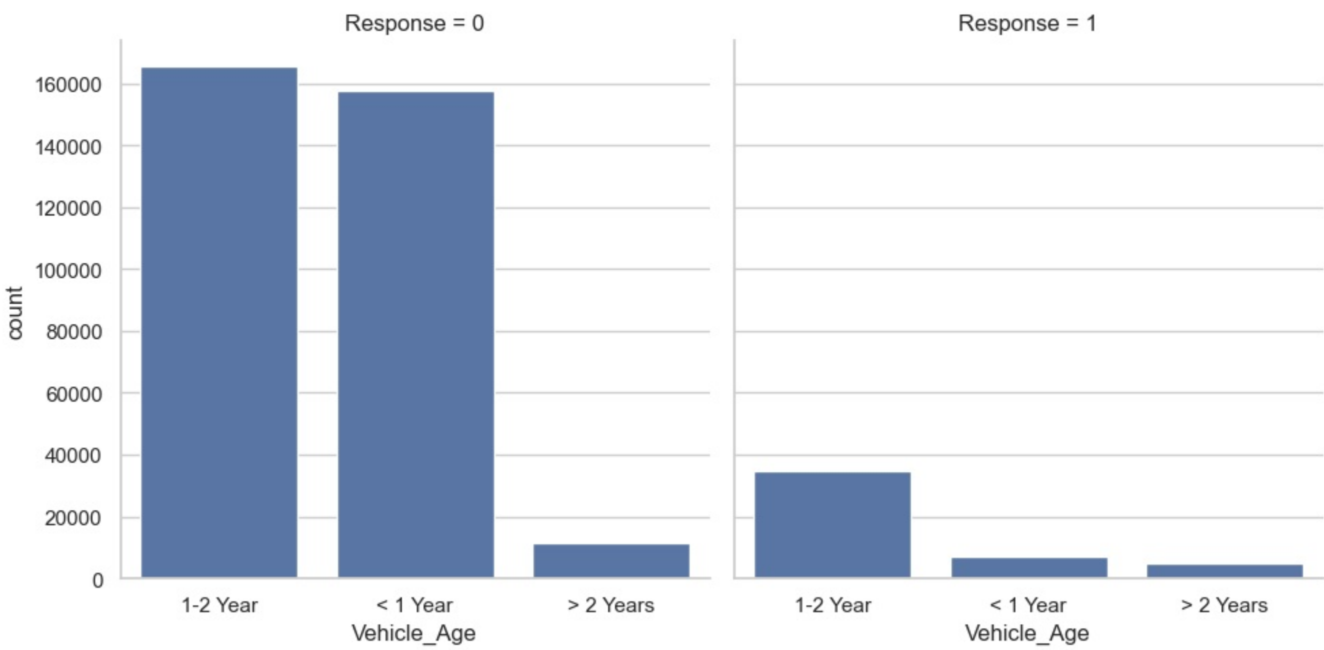
Risk-Based Pricing: Implement a risk-based pricing model that considers vehicle age as a key factor. Older vehicles may have higher repair costs and increased risk of accidents, so adjusting premiums accordingly can help optimize pricing.

In [141…
```
df3=df.groupby(['Vehicle_Age','Response'])['id'].count().to_frame().rename(columns={'id':'count'}).reset_index(
df3
```

Out[141…

	Vehicle_Age	Response	count
0	1-2 Year	0	165510
1	1-2 Year	1	34806
2	< 1 Year	0	157584
3	< 1 Year	1	7202
4	> 2 Years	0	11305
5	> 2 Years	1	4702

In [143…
```
sns.catplot(x="Vehicle_Age",y="count",col="Response",data=df3,kind="bar")
plt.show()
```



Observations:

The distribution of vehicle age is similar for both response groups (0 and 1).

However, the proportion of customers with vehicles less than a year old is slightly higher among those who responded positively to marketing campaigns.

Recommendations:

Targeted Marketing: Focus on targeting customers with newer vehicles, as they seem to be more receptive to marketing campaigns.

Personalized Offers: Tailor marketing messages and offers to the specific needs and preferences of customers with different vehicle ages.

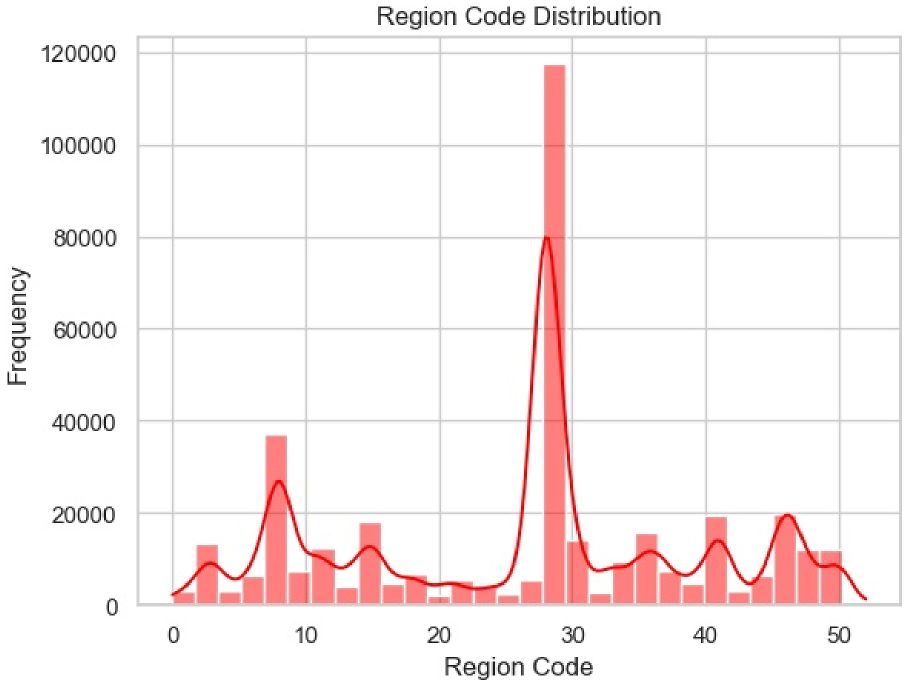
Incentives for New Vehicle Owners: Offer special discounts or incentives to customers who have recently purchased a new vehicle to encourage them to choose your insurance provider.

Step 11: Region-wise Analysis:

Analyze patterns in Region Code to understand claim distribution by Region.

Region Code Distribution

In [147…
```
sns.histplot(df['Region_Code'],bins=30,kde=True,color='red')
plt.title("Region Code Distribution")
plt.xlabel("Region Code")
plt.ylabel("Frequency")
plt.show()
```



Observations:

The region code distribution shows multiple peaks and valleys, indicating varying levels of customer activity across different regions. There are specific regions with significantly higher customer concentrations.

Recommendations:

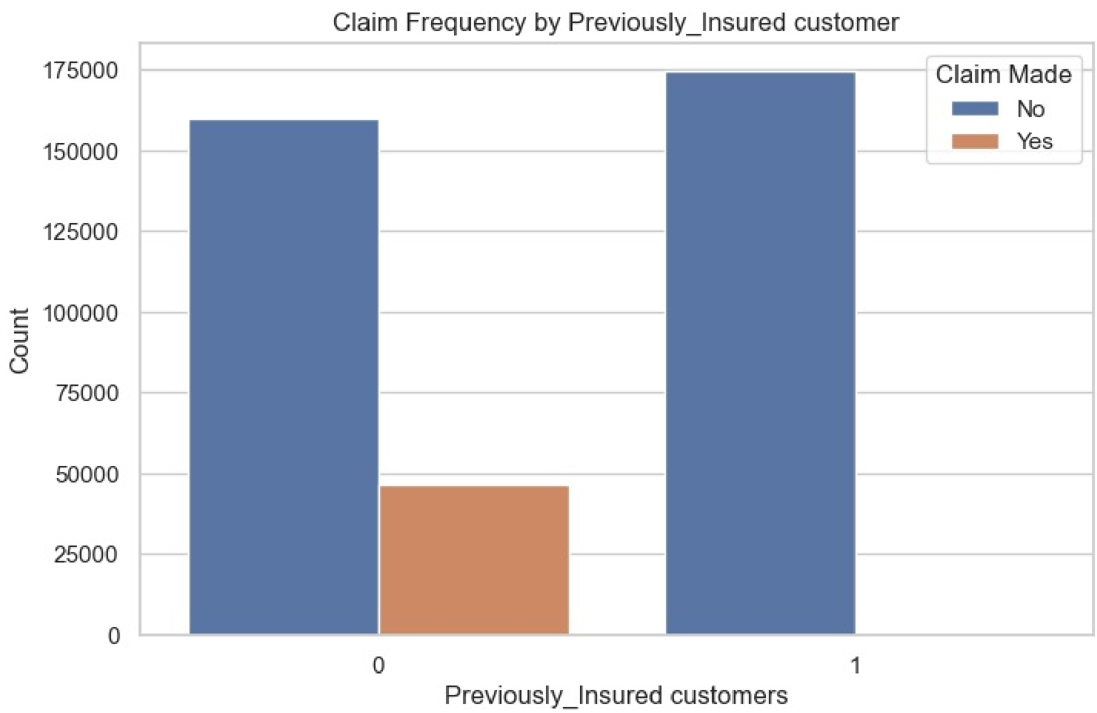
Targeted Marketing: Analyze the performance of different regions and focus marketing efforts on regions with higher potential.

Regional Pricing: Consider implementing region-specific pricing strategies to account for differences in risk factors and customer preferences.

Local Partnerships: Partner with local businesses and organizations to expand your reach and build brand awareness in specific regions.

Step 11: Customer Loyalty Analysis:

In [182…
```
plt.figure(figsize=(8, 5))
sns.countplot(x='Previously_Insured', hue='Response', data=df)
plt.title('Claim Frequency by Previously_Insured customer')
plt.xlabel('Previously_Insured customers')
plt.ylabel('Count')
plt.legend(title='Claim Made', labels=['No', 'Yes'])
plt.show()
```



Observations:

The chart shows that a higher proportion of previously insured customers have made claims compared to those who were not previously insured. This suggests that customers with prior insurance experience may have a higher risk profile.

Recommendations:

Risk-Based Pricing: Implement a risk-based pricing model that takes into account factors like prior insurance history and claim frequency.

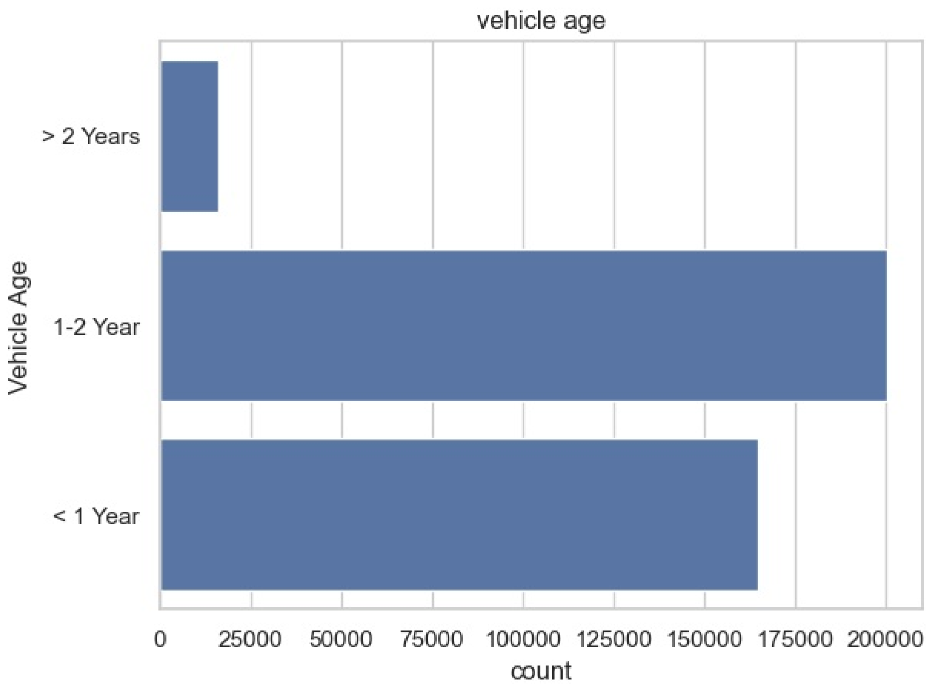
Customer Segmentation: Segment customers based on their claim history and offer tailored insurance products and pricing.

Step 12: Claim Frequency by Vehicle Damage

Investigate how Vehicle Damage affects the frequency of claims.

In [151…

```
sns.countplot(df.Vehicle_Age)
plt.title("vehicle age")
plt.ylabel("Vehicle Age")
plt.show()
```



Observations:

The majority of vehicles in the dataset are less than a year old, followed by vehicles between 1 and 2 years old. Vehicles older than 2 years represent the smallest proportion.

Recommendations:

Targeted Marketing: Focus on targeting customers with newer vehicles, as they represent a significant portion of the market. Offer competitive pricing and value-added services to attract and retain these customers.

Risk-Based Pricing: Implement a risk-based pricing model that considers vehicle age as a key factor. Older vehicles may have higher repair costs and increased risk of accidents, so adjusting premiums accordingly can help optimize pricing.

Conclusion

The analysis highlights key patterns across demographics, vehicle attributes, and customer behavior, emphasizing the importance of tailored marketing, risk-based pricing, and customer retention strategies. Younger customers and newer vehicles dominate the dataset, presenting opportunities for targeted campaigns and personalized offerings. Addressing class imbalances and optimizing regional and channel-specific approaches can significantly enhance engagement and business outcomes.

In [ ]:
```

```