Insurance Exploratory Data Analysis (EDA)

This notebook explores the cleaned insurance dataset to uncover **premium drivers, customer segments,**
and retention opportunities. It moves beyond cleaning into visualization, correlation, and clustering to derive actionable business insights.

Project Overview

- **Business Context**
  After cleaning and wrangling, the next step is to identify key factors influencing insurance premiums and to discover natural customer segments for pricing and marketing.
- **Goal**
  Use descriptive statistics, visualization, and clustering to:
  1. Understand premium distribution and drivers,
  2. Segment customers by risk and revenue potential,
  3. Highlight actionable insights for retention and upsell.
- **Deliverable**
  Key visuals, cluster profiles, and a ranked list of premium drivers.

1. Load and Inspect the Data

In [17]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset
df = pd.read_csv("data/Insurance.csv")

# Preview structure
print("Shape:", df.shape)
print("\nColumn Info:")
print(df.info())
df.head()
```

```
Shape: (2082, 23)

Column Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2082 entries, 0 to 2081
Data columns (total 23 columns):
 #   Column                           Non-Null Count  Dtype
---  ------                           --------------  -----
 0   Customer ID                      2082 non-null   int64
 1   Age                              2082 non-null   int64
 2   Gender                           2082 non-null   object
 3   Marital Status                   2082 non-null   object
 4   Occupation                       2082 non-null   object
 5   Income Level                     2082 non-null   int64
 6   Education Level                  2082 non-null   object
 7   Geographic Information           2082 non-null   object
 8   Location                         2082 non-null   int64
 9   Purchase History                 2082 non-null   object
 10  Policy Start Date                2082 non-null   object
 11  Policy Renewal Date              2082 non-null   object
 12  Claim History                    2082 non-null   int64
 13  Coverage Amount                  2082 non-null   int64
 14  Premium Amount                   2082 non-null   int64
 15  Deductible                       2082 non-null   int64
 16  Policy Type                      2082 non-null   object
 17  Preferred Communication Channel  2082 non-null   object
 18  Preferred Contact Time           2082 non-null   object
 19  Risk Profile                     2082 non-null   int64
 20  Credit Score                     2082 non-null   int64
 21  Driving Record                   2082 non-null   object
 22  Life Events                      2082 non-null   object
dtypes: int64(10), object(13)
memory usage: 374.2+ KB
None
```

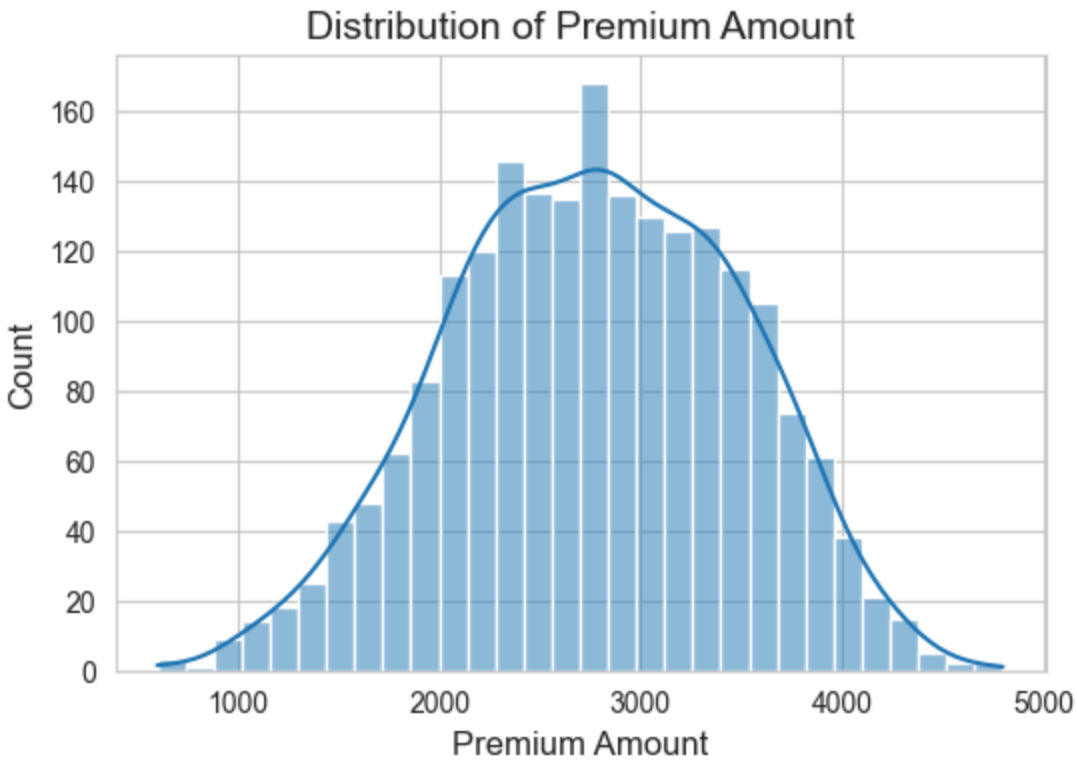
Out[17]:

	Customer ID	Age	Gender	Marital Status	Occupation	Income Level	Education Level	Geographic Information	Locati
0	15043	48	Female	Single	Engineer	72654	Associate Degree	Karnataka	751
1	88777	50	Male	Divorced	Manager	93448	Master's Degree	Karnataka	567
2	62911	53	Male	Widowed	Doctor	92558	Doctorate	Arunachal Pradesh	602
3	38955	38	Male	Widowed	Salesperson	78536	High School Diploma	Andhra Pradesh	347
4	3935	42	Male	Married	Salesperson	90220	High School Diploma	Puducherry	142

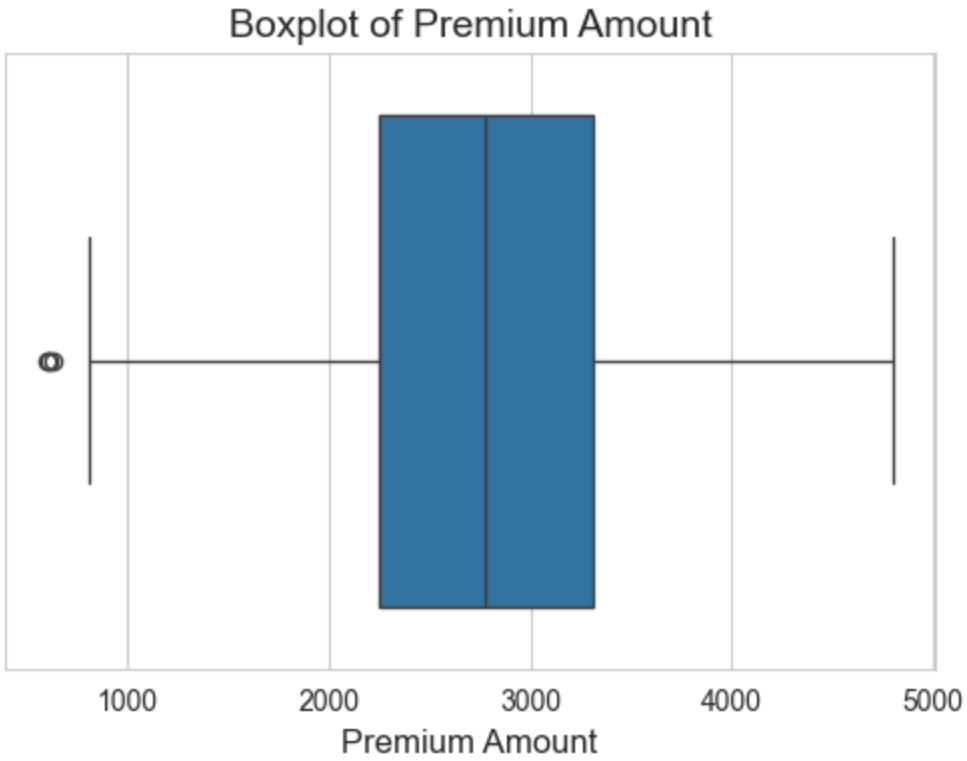
5 rows × 23 columns

2. Premium Drivers – Explore the Target

In [21]:
```
# Histogram of Premium Amount
plt.figure(figsize=(6,4))
sns.histplot(df['Premium Amount'], bins=30, kde=True)
plt.title("Distribution of Premium Amount")
plt.savefig("charts/premium_distribution.png", dpi=300, bbox_inches='tight')
plt.show()
```

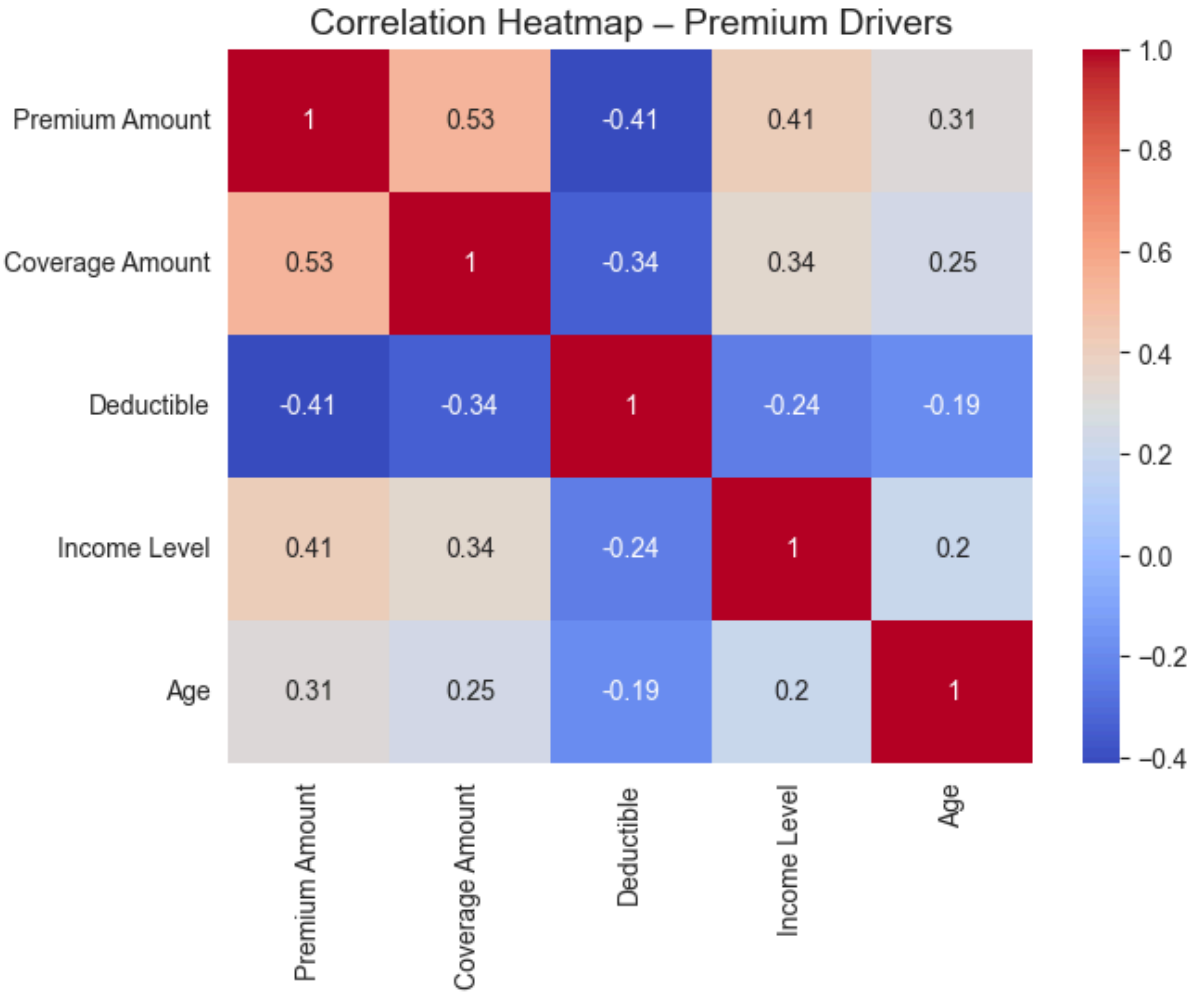


In [22]:
```
# Boxplot of Premium Amount
plt.figure(figsize=(6,4))
sns.boxplot(x=df['Premium Amount'])
plt.title("Boxplot of Premium Amount")
plt.savefig("charts/premium_boxplot.png", dpi=300, bbox_inches='tight')
plt.show()
```



The premium distribution is roughly bell-shaped, centered around **~3,000**, with most policies between **2,000 and 3,500**. A few **low-premium outliers** fall below about 1,000, and only a small tail extends above 4,500. This indicates a fairly tight pricing range with a small set of minimal-coverage customers and a modest high-end segment for potential upsell.

In [28]:
```
# Correlations with Numeric Drivers
num_cols = ['Premium Amount','Coverage Amount','Deductible','Income Level','Age']
sns.heatmap(df[num_cols].corr(), annot=True, cmap="coolwarm")
plt.title("Correlation Heatmap – Premium Drivers")
plt.savefig("charts/Correlations.png", dpi=300, bbox_inches='tight')
plt.show()
```



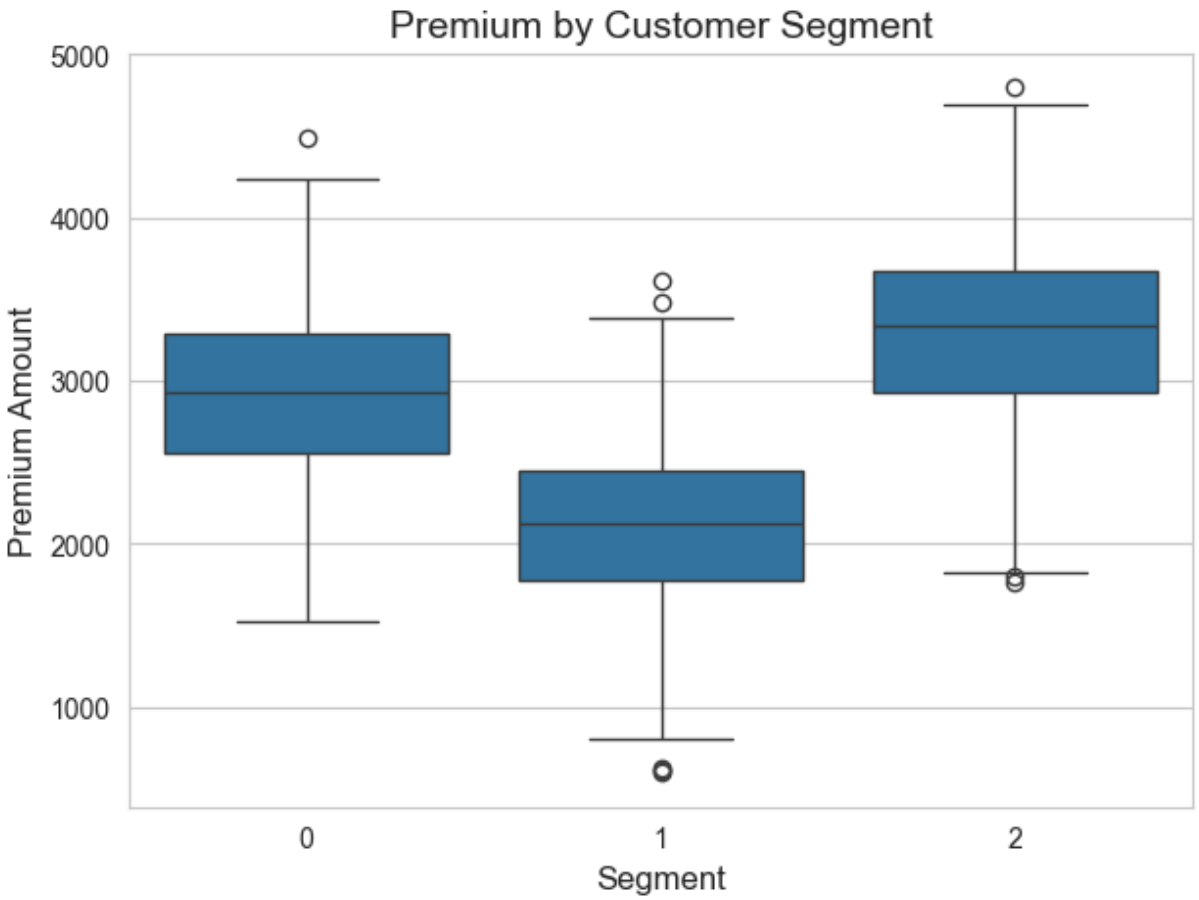
Premium amount rises strongly with **coverage** and **income**, while it drops as **deductible** increases. Age shows only a mild positive link, suggesting price is driven more by policy size and customer income than by age.

3. Risk vs Revenue Segments – Clustering

In [32]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans

features = df[['Premium Amount','Coverage Amount','Deductible','Age']]
```

```
scaled = StandardScaler().fit_transform(features)

kmeans = KMeans(n_clusters=3, random_state=42)
df['Segment'] = kmeans.fit_predict(scaled)
# Average values for key drivers in each segment
segment_profile = (
    df.groupby('Segment')[['Premium Amount',
                           'Coverage Amount',
                           'Deductible',
                           'Age']]
      .mean()
      .round(0)
)
display(segment_profile)


sns.boxplot(x='Segment', y='Premium Amount', data=df)
plt.title("Premium by Customer Segment")
plt.savefig("charts/Segment.png", dpi=300, bbox_inches='tight')
plt.show()
```

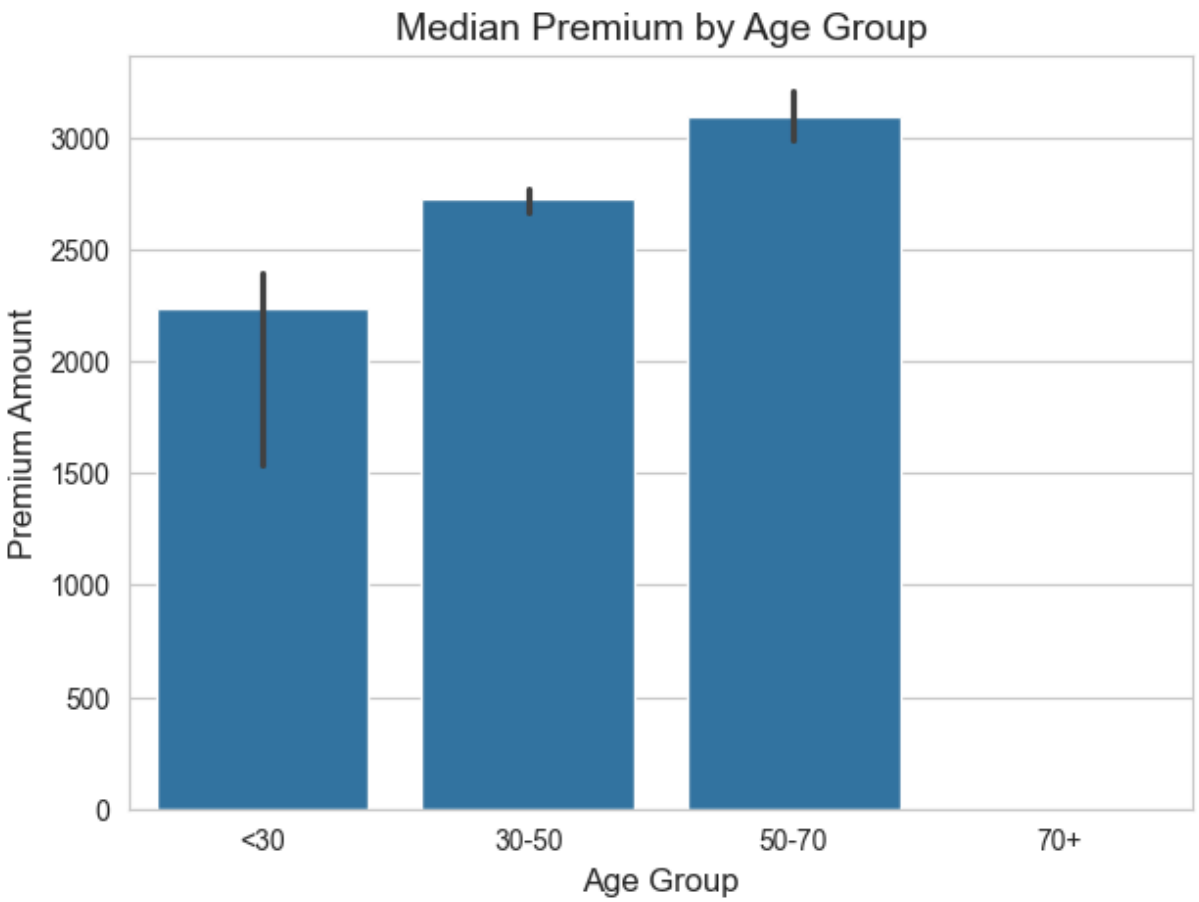
Segment	Premium Amount	Coverage Amount	Deductible	Age
0	2930.0	562287.0	1186.0	42.0
1	2099.0	401575.0	1367.0	43.0
2	3305.0	590010.0	1131.0	50.0



- Segment 2 represents high-revenue, higher-risk customers with the largest premiums and coverage but the smallest deductibles.
- Segment 1 are budget customers with the lowest premiums and highest deductibles.
- Segment 0 sits in between, offering balanced revenue and risk.

4. Retention & Upsell Indicators

In [33]:
```
# Cross-tab with communication channel
pd.crosstab(df['Segment'], df['Preferred Communication Channel'],
            normalize='index')*100

# Age group or occupation if present
if 'Age' in df.columns:
    age_bins = [0,30,50,70,100]
    df['Age Group'] = pd.cut(df['Age'], bins=age_bins,
                             labels=['<30','30-50','50-70','70+'])
    sns.barplot(x='Age Group', y='Premium Amount', data=df, estimator=np.median)
    plt.title("Median Premium by Age Group")
    plt.show()
```



The black lines represent a bootstrap confidence interval (by default 95%) for the median premium in each age group. They give a quick visual cue of how stable the median estimate is: Short bars → the median is precise (low variability). Tall bars → more spread in the data or fewer samples, so the median is less certain.

Insight: Premiums tend to increase steadily with age, peaking in the 50–70 group. Older customers therefore represent a higher-value segment for targeted retention or upsell campaigns.

Summary

- The analysis shows that coverage amount and deductible are the strongest premium drivers, with income and age having smaller effects.
- Clustering customers reveals a high-revenue segment (high coverage, low deductible), a balanced mid-range group, and a low-value basic group, helping target pricing and marketing.
- Premiums also rise steadily with age, highlighting middle-aged and older customers as key opportunities for retention and upsell.