Project Overview

Project Title

Analyzing Health Risk Indicators and Predicting Insurance Premiums Using Statistical and Machine Learning Techniques

Objective

The primary objective of this project is to apply a combination of descriptive statistics, inferential statistics, and predictive modeling to analyze how health-related factors affect insurance premium pricing. Using a dataset of 986 individuals with multiple health indicators, we aim to:

1. **Explore** the data structure, distributions, and relationships between variables.
2. **Test hypotheses** about the impact of chronic conditions and surgeries on premium costs.
3. **Estimate confidence intervals** around population-level statistics.
4. **Build regression models** to predict premium prices.
5. **Classify individuals** as diabetic or non-diabetic using machine learning.
6. **Cluster individuals** into health risk segments using unsupervised learning.

Skills Demonstrated

This project reflects core competencies developed throughout the course:

- Descriptive and inferential statistics
- Probability distribution modeling
- Confidence and prediction intervals
- Linear and Generalized Linear Models (GLMs)
- Hypothesis testing (means, proportions)
- Classification metrics: accuracy, precision, recall, AUROC
- Unsupervised learning using KMeans clustering
- Data visualization and interpretation
- End-to-end Python implementation using libraries such as:
  - `pandas`, `numpy`, `scipy`, `matplotlib`, `seaborn`, `sklearn`, `statsmodels`

Methodology Overview

1. **Data Understanding**
   Inspect dataset shape, types, and missing values. Use descriptive statistics and visualizations.
2. **Exploratory Data Analysis**
   Visualize distributions, correlations, and relationships among features and target variable (`PremiumPrice`).
3. **Hypothesis Testing**
   Test whether variables like `Diabetes`, `ChronicDiseases`, or `Surgeries` significantly impact premium cost.
4. **Regression Modeling**
   Use linear regression and GLM to model `PremiumPrice` as a function of relevant health factors.
5. **Classification**
   Build a random forest model to classify whether an individual is diabetic using health features.
6. **Clustering**
   Apply KMeans to discover natural groupings in the population based on health and premium attributes.

Expected Outcomes

- Identification of key factors that statistically and practically influence insurance premium cost.
- Accurate prediction models for premium pricing.
- Diagnostic tools for insurers to identify high-risk groups.
- Enhanced understanding of statistical foundations and their real-world application in health insurance analytics.

Library Import

In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.ensemble import RandomForestClassifier
import statsmodels.api as sm
```

In [2]:
```python
pd.set_option('display.float_format', lambda x: '%.2f' % x)
sns.set(style="whitegrid")
```

Dataset Overview

Dataset Summary

- **Number of Rows (Observations):** 986
- **Number of Columns (Features):** 11
- **Data Type:** All columns are of integer type (`int64`), implying the dataset contains purely numerical values — likely binary flags or counts — suitable for statistical modeling and machine learning.

Variable Descriptions

Column Name	Description
`Age`	Age of the individual (in years).
`Diabetes`	Binary indicator of whether the individual has diabetes (1 = Yes, 0 = No).
`BloodPressureProblems`	Binary flag indicating blood pressure-related issues.
`AnyTransplants`	Binary indicator for history of organ transplants.
`AnyChronicDiseases`	Binary flag for chronic disease conditions (e.g., asthma, arthritis).
`Height`	Height of the individual (in centimeters).
`Weight`	Weight of the individual (in kilograms).
`KnownAllergies`	Binary flag for whether individual has known allergies.
`HistoryOfCancerInFamily`	Binary flag indicating family history of cancer.
`NumberOfMajorSurgeries`	Count of major surgeries undergone by the individual.
`PremiumPrice`	Annual health insurance premium (in local currency, likely INR).

Key Characteristics

- The dataset is suitable for:
  - **Descriptive statistical analysis**
  - **Hypothesis testing**
  - **Regression modeling**
  - **Classification and clustering**
- No missing values or non-numeric entries are present, simplifying preprocessing.
- Binary columns can be treated as categorical features during modeling.

Analytical Goals

- Understand which health indicators most strongly influence premium pricing.
- Test assumptions about health risks and insurance costs.
- Build models to predict premiums and health conditions.
- Cluster individuals into risk groups for potential policy segmentation.

In [3]:
```python
df = pd.read_csv("Medicalpremium.csv")

print("Dataset Shape:", df.shape)
print("\nColumn Types:")
print(df.dtypes)
print("\nMissing Values:")
print(df.isnull().sum())
```

```
Dataset Shape: (986, 11)

Column Types:
Age                        int64
Diabetes                   int64
BloodPressureProblems      int64
AnyTransplants             int64
AnyChronicDiseases         int64
Height                     int64
Weight                     int64
KnownAllergies             int64
HistoryOfCancerInFamily    int64
NumberOfMajorSurgeries     int64
PremiumPrice               int64
dtype: object

Missing Values:
Age                        0
Diabetes                   0
BloodPressureProblems      0
AnyTransplants             0
AnyChronicDiseases         0
Height                     0
Weight                     0
KnownAllergies             0
HistoryOfCancerInFamily    0
NumberOfMajorSurgeries     0
PremiumPrice               0
dtype: int64
```

In [7]:
```python
df.head()
```

Out[7]:

	Age	Diabetes	BloodPressureProblems	AnyTransplants	AnyChronicDiseases	Height	Weight	KnownAllergies	HistoryOfCancerInFamily	Num
0	45	0	0	0	0	155	57	0	0	
1	60	1	0	0	0	180	73	0	0	
2	36	1	1	0	0	158	59	0	0	
3	52	1	1	0	1	183	93	0	0	
4	38	0	0	0	1	166	88	0	0	

1. Descriptive and Exploratory Data Analysis

Objective

To understand the basic structure, distribution, and central tendencies of the dataset variables.

Key Concepts

- **Five Number Summary**: Minimum, Q1, Median, Q3, Maximum
- **Measures of Central Tendency**: Mean, Median, Mode
- **Measures of Dispersion**: Range, Interquartile Range (IQR), Standard Deviation, Variance

Formulas

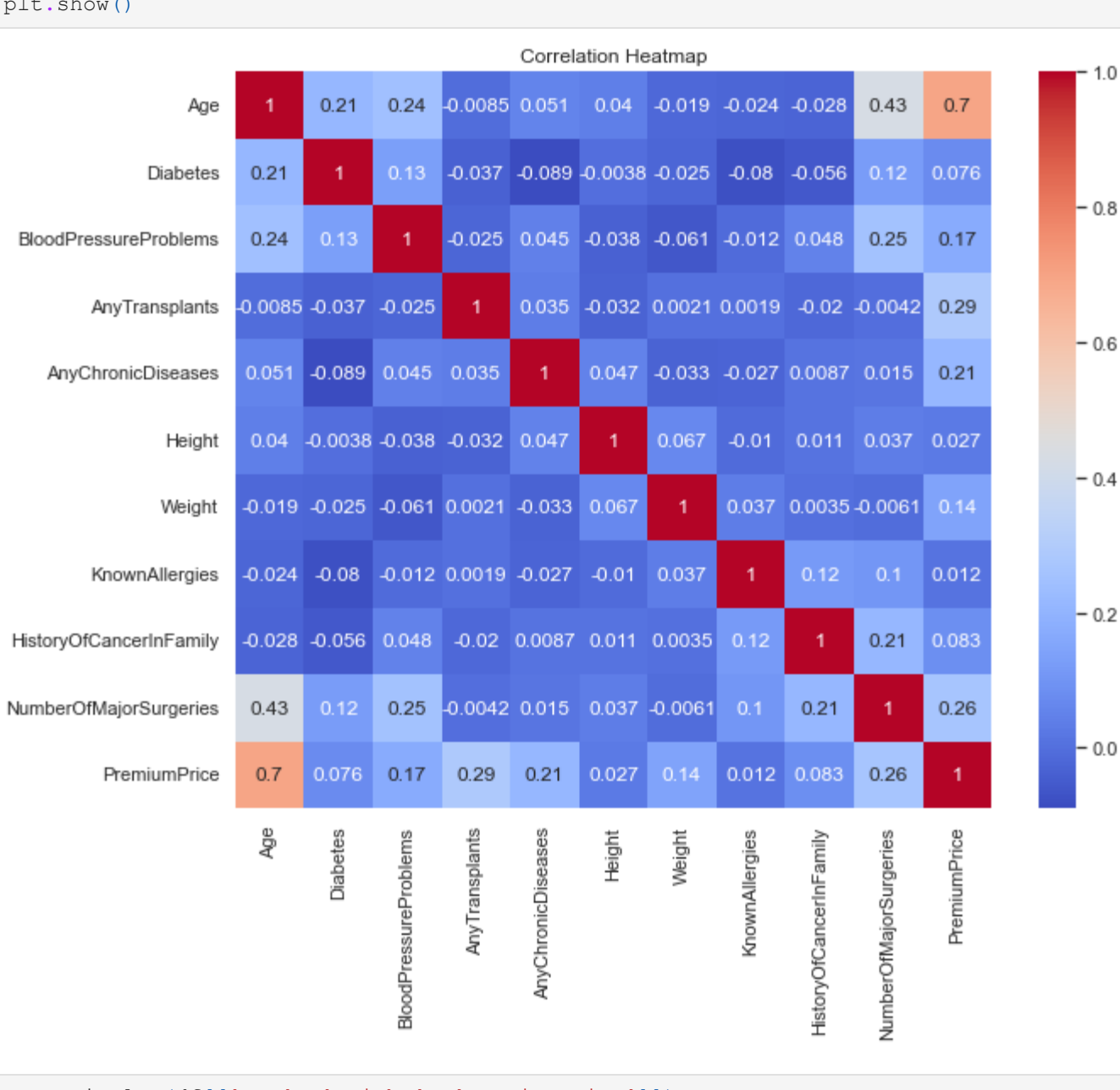
- **Mean**: ($\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$)
- **Standard Deviation**: (s = $\sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2}$)
- **IQR**: ($\text{IQR} = Q3 - Q1$)

We will use descriptive plots (histograms, boxplots, pairplots) and statistical summaries to visualize data distributions and identify potential outliers or skewness.

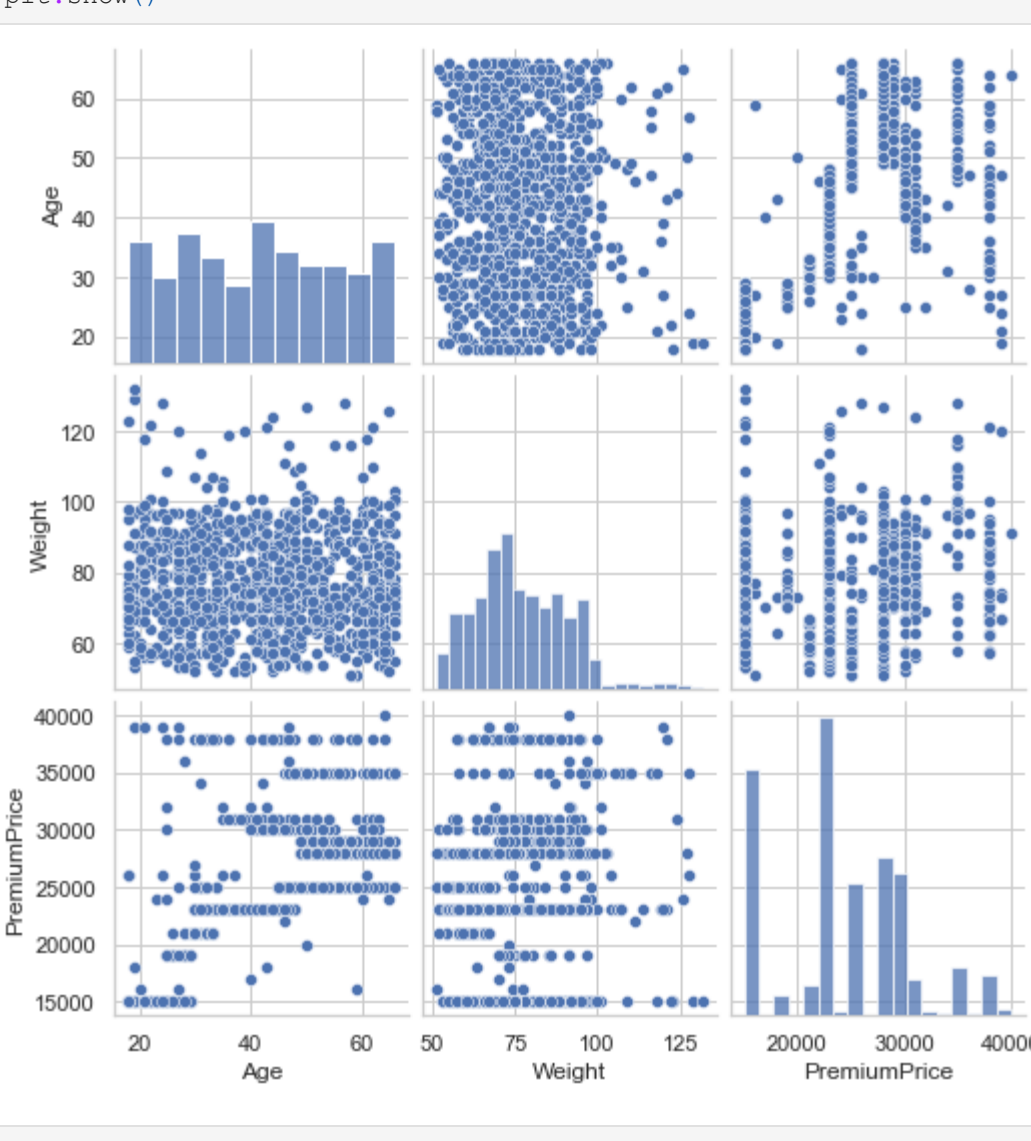
In [4]:
```python
print("\nDescriptive Statistics:")
print(df.describe())
print("\nFive Number Summary:")
print(df.quantile([0, 0.25, 0.5, 0.75, 1]))
```

```
Descriptive Statistics:
         Age  Diabetes  BloodPressureProblems  AnyTransplants  \
count 986.00    986.00                 986.00          986.00
mean   41.75      0.42                   0.47            0.06
std    13.96      0.49                   0.50            0.23
min    18.00      0.00                   0.00            0.00
25%    30.00      0.00                   0.00            0.00
50%    42.00      0.00                   0.00            0.00
75%    53.00      1.00                   1.00            0.00
max    66.00      1.00                   1.00            1.00

       AnyChronicDiseases  Height  Weight  KnownAllergies  \
count              986.00  986.00  986.00          986.00
mean                 0.18  168.18   76.95            0.22
std                  0.38   10.10   14.27            0.41
min                  0.00  145.00   51.00            0.00
25%                  0.00  161.00   67.00            0.00
50%                  0.00  168.00   75.00            0.00
75%                  0.00  176.00   87.00            0.00
max                  1.00  188.00  132.00            1.00

       HistoryOfCancerInFamily  NumberOfMajorSurgeries  PremiumPrice
count                   986.00                  986.00        986.00
mean                      0.12                    0.67      24336.71
std                       0.32                    0.75       6248.18
min                       0.00                    0.00      15000.00
25%                       0.00                    0.00      21000.00
50%                       0.00                    1.00      23000.00
75%                       0.00                    1.00      28000.00
max                       1.00                    3.00      40000.00

Five Number Summary:
       Age  Diabetes  BloodPressureProblems  AnyTransplants  \
0.00 18.00      0.00                   0.00            0.00
0.25 30.00      0.00                   0.00            0.00
0.50 42.00      0.00                   0.00            0.00
0.75 53.00      1.00                   1.00            0.00
1.00 66.00      1.00                   1.00            1.00

      AnyChronicDiseases  Height  Weight  KnownAllergies  \
0.00                0.00  145.00   51.00            0.00
0.25                0.00  161.00   67.00            0.00
0.50                0.00  168.00   75.00            0.00
0.75                0.00  176.00   87.00            0.00
1.00                1.00  188.00  132.00            1.00

      HistoryOfCancerInFamily  NumberOfMajorSurgeries  PremiumPrice
0.00                     0.00                    0.00      15000.00
0.25                     0.00                    0.00      21000.00
0.50                     0.00                    1.00      23000.00
0.75                     0.00                    1.00      28000.00
1.00                     1.00                    3.00      40000.00
```

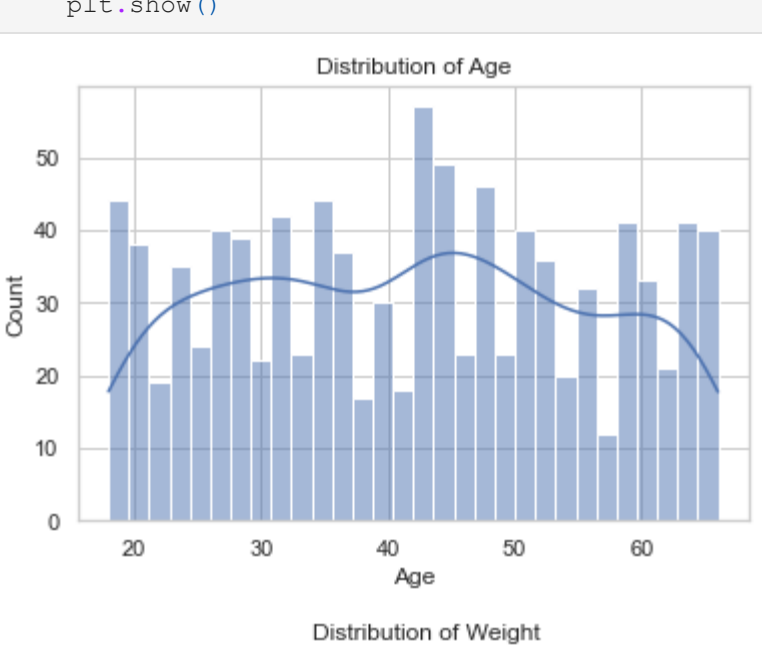
In [5]:
```python
corr = df.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(corr, annot=True, cmap="coolwarm")
plt.title("Correlation Heatmap")
plt.show()
```

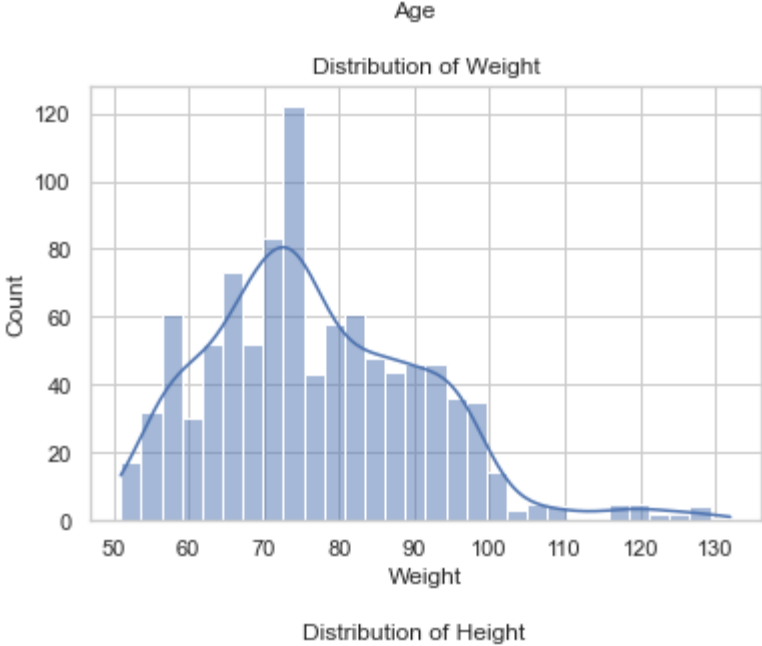


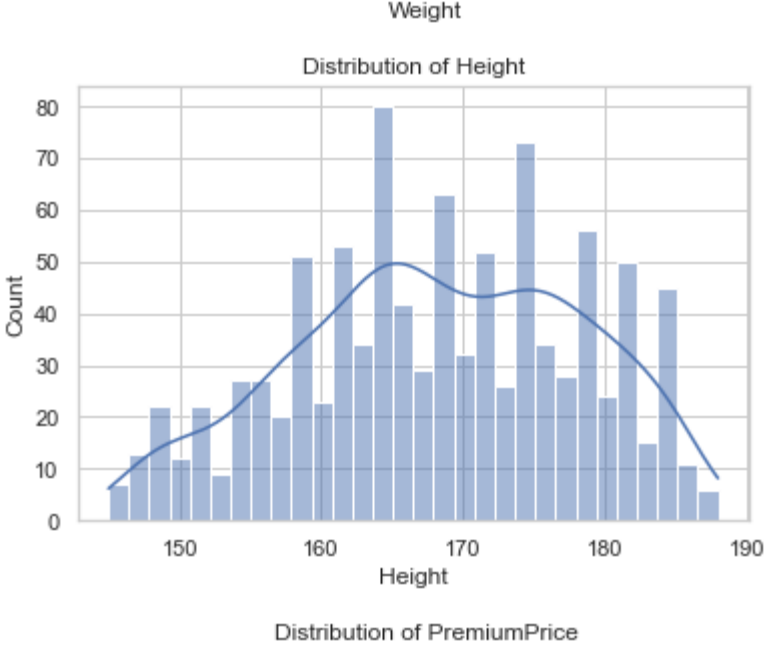
In [11]:
```python
sns.pairplot(df[['Age', 'Weight', 'PremiumPrice']])
plt.show()
```

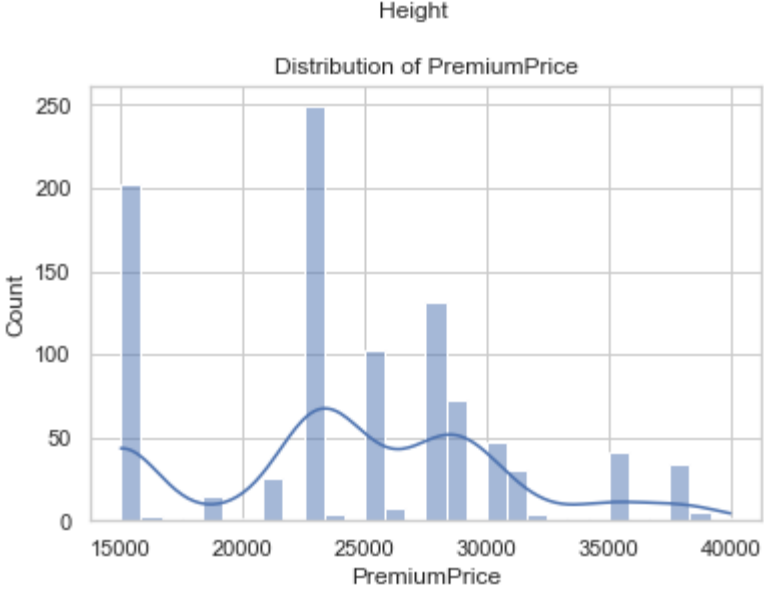


In [9]:
```python
for col in ['Age', 'Weight', 'Height', 'PremiumPrice']:
    plt.figure(figsize=(6, 4))
    sns.histplot(df[col], kde=True, bins=30)
    plt.title(f"Distribution of {col}")
    plt.show()
```

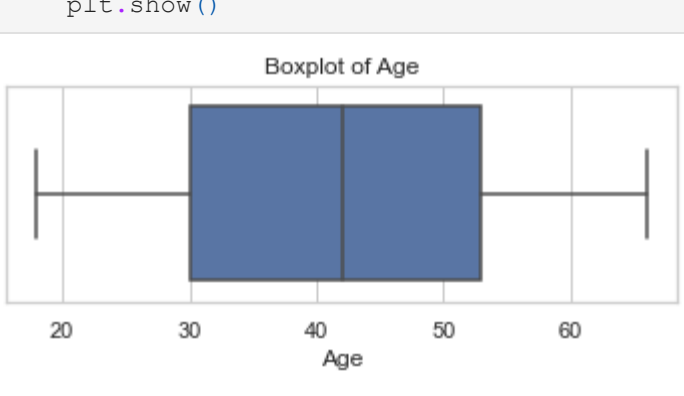


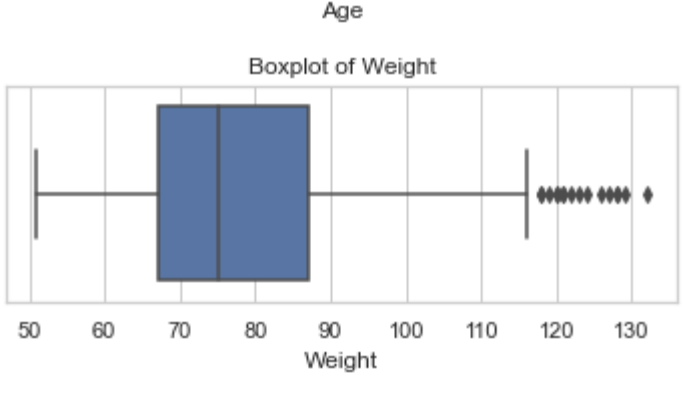


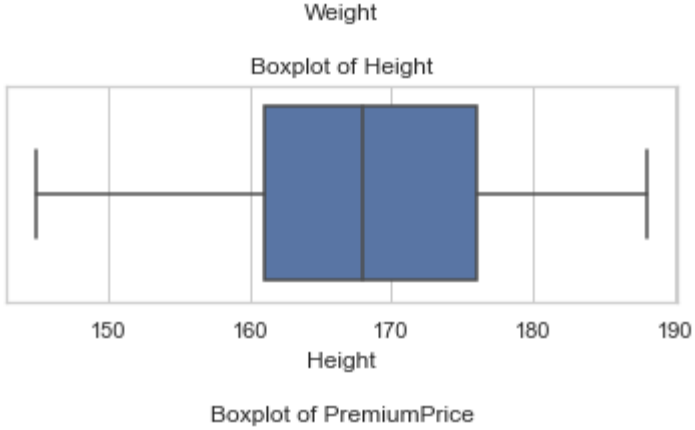


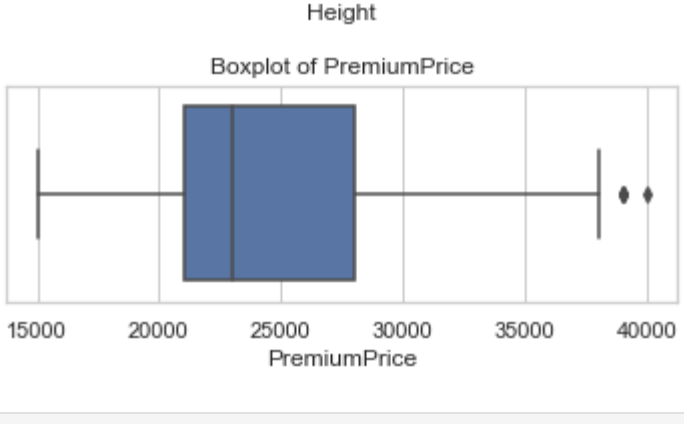


In [12]:
```python
for col in ['Age', 'Weight', 'Height', 'PremiumPrice']:
    plt.figure(figsize=(6, 2))
    sns.boxplot(data=df, x=col)
    plt.title(f"Boxplot of {col}")
    plt.show()
```

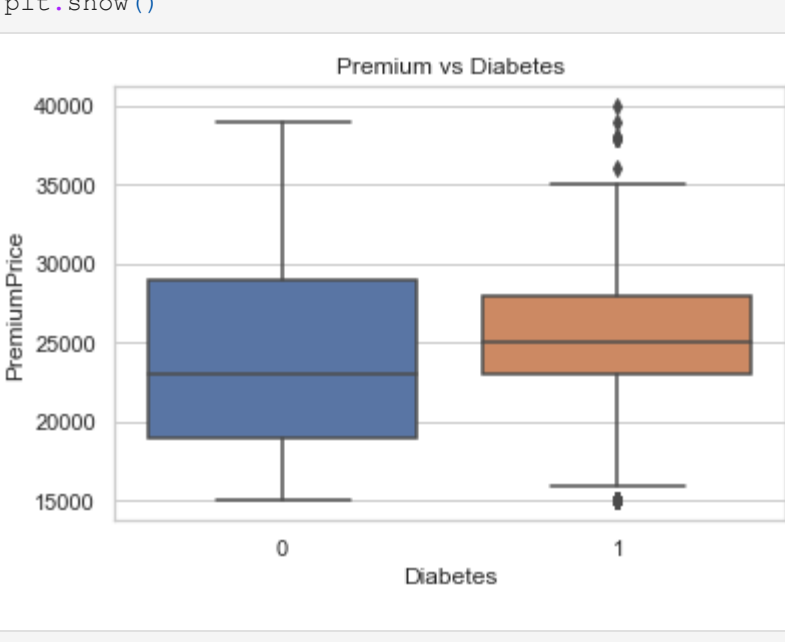








In [13]:
```python
df['BMI'] = df['Weight'] / ((df['Height'] / 100) ** 2)

# Premium vs Diabetes
sns.boxplot(data=df, x='Diabetes', y='PremiumPrice')
plt.title('Premium vs Diabetes')
plt.show()
```

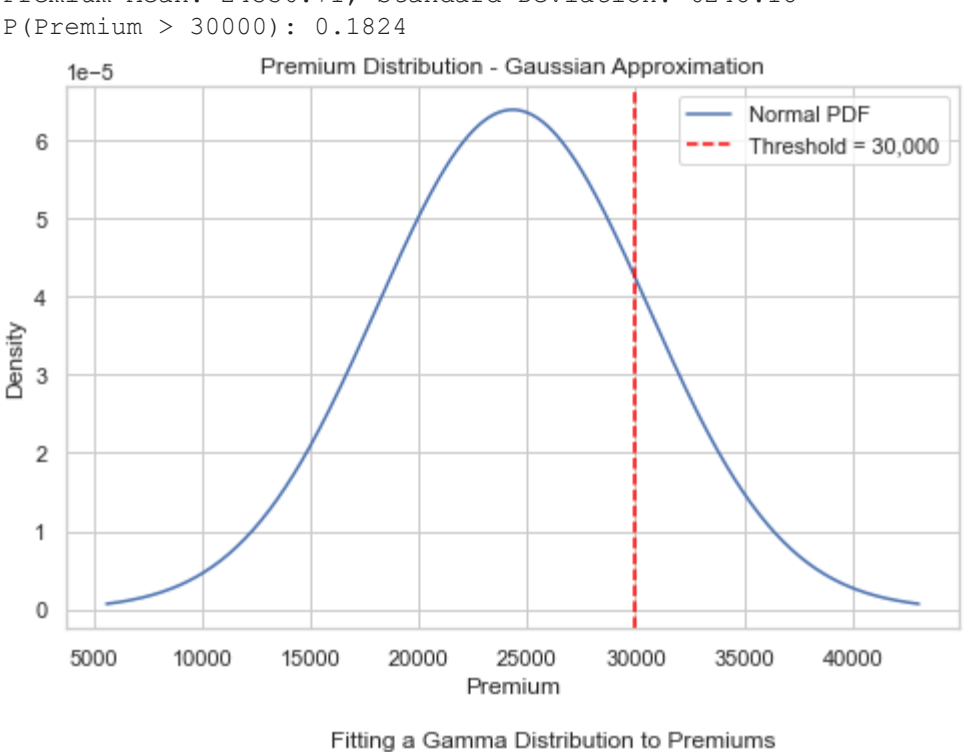


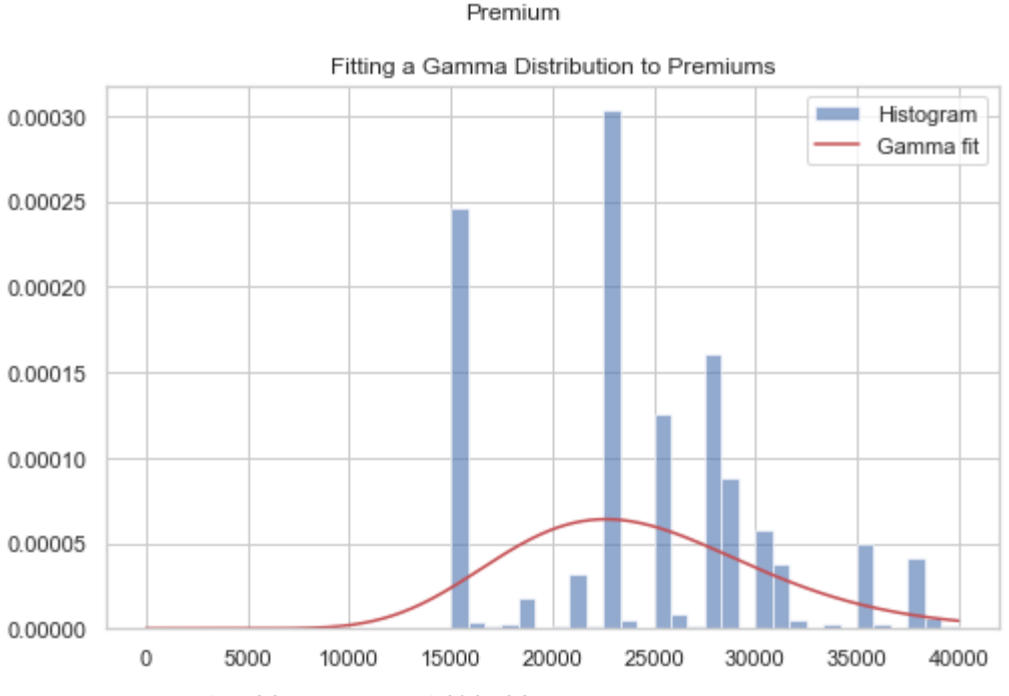
In [14]:
```python
from scipy.stats import binom, poisson, norm

p_diabetes = df['Diabetes'].mean()
binom_prob = binom.pmf(3, 10, p_diabetes)
print(f"P(Exactly 3 of 10 people have Diabetes): {binom_prob:.4f}")

mu = df['PremiumPrice'].mean()
sigma = df['PremiumPrice'].std()
print("P(PremiumPrice > 30000):", 1 - norm.cdf(30000, mu, sigma))
```

```
P(Exactly 3 of 10 people have Diabetes): 0.1964
P(PremiumPrice > 30000): 0.18236497912412053
```

In [22]:
```python
from scipy.stats import binom, poisson, norm

# Binomial Distribution: Diabetes prevalence
p_diabetes = df['Diabetes'].mean()
print(f"Estimated P(Diabetes): {p_diabetes:.2f}")

binom_prob = binom.pmf(3, 10, p_diabetes)
print(f"P(Exactly 3 out of 10 people have Diabetes): {binom_prob:.4f}")

# Poisson Distribution: Approximate count events like surgeries
lambda_surgery = df['NumberOfMajorSurgeries'].mean()
poisson_prob = poisson.pmf(2, lambda_surgery)
print(f"P(Exactly 2 surgeries given lambda={lambda_surgery:.2f}): {poisson_prob:.4f}")

# Gaussian Distribution: Premium distribution
mu = df['PremiumPrice'].mean()
sigma = df['PremiumPrice'].std()
print(f"Premium Mean: {mu:.2f}, Standard Deviation: {sigma:.2f}")

# Probability of paying more than 30,000 in premium
p_above_30k = 1 - norm.cdf(30000, mu, sigma)
print(f"P(Premium > 30000): {p_above_30k:.4f}")

# Visual comparison
x_vals = np.linspace(mu - 3*sigma, mu + 3*sigma, 500)
y_vals = norm.pdf(x_vals, mu, sigma)
plt.figure(figsize=(8, 5))
plt.plot(x_vals, y_vals, label='Normal PDF')
plt.axvline(30000, color='red', linestyle='--', label='Threshold = 30,000')
plt.title("Premium Distribution - Gaussian Approximation")
plt.xlabel("Premium")
plt.ylabel("Density")
plt.legend()
plt.show()

# Gamma Distribution fit
from scipy.stats import gamma
shape, loc, scale = gamma.fit(df['PremiumPrice'], floc=0)
x = np.linspace(0, df['PremiumPrice'].max(), 500)
plt.figure(figsize=(8, 5))
plt.hist(df['PremiumPrice'], bins=30, density=True, alpha=0.6, label='Histogram')
plt.plot(x, gamma.pdf(x, shape, loc, scale), 'r-', label=f'Gamma fit')
plt.title("Fitting a Gamma Distribution to Premiums")
plt.legend()
plt.show()

print(f"Gamma shape: {shape:.2f}, scale: {scale:.2f}")
```

```
Estimated P(Diabetes): 0.42
P(Exactly 3 out of 10 people have Diabetes): 0.1964
P(Exactly 2 surgeries given lambda=0.67): 0.1142
Premium Mean: 24336.71, Standard Deviation: 6248.18
P(Premium > 30000): 0.1824
```






```
Gamma shape: 14.38, scale: 1692.83
```

Interpretation

- Premium prices show a strong right skew, indicating the presence of high-value outliers.
- Diabetic status and number of surgeries appear visually linked with higher premiums.
- Correlation matrix suggests Age, BMI, and Surgeries are moderately correlated with Premium, justifying their use in modeling.

2. Confidence Interval Estimation

Objective

To estimate the range of plausible values for the population mean premium or BMI.

Formula for 95% CI:

$$CI = \bar{x} \pm t^* \cdot \frac{s}{\sqrt{n}}$$

Where:

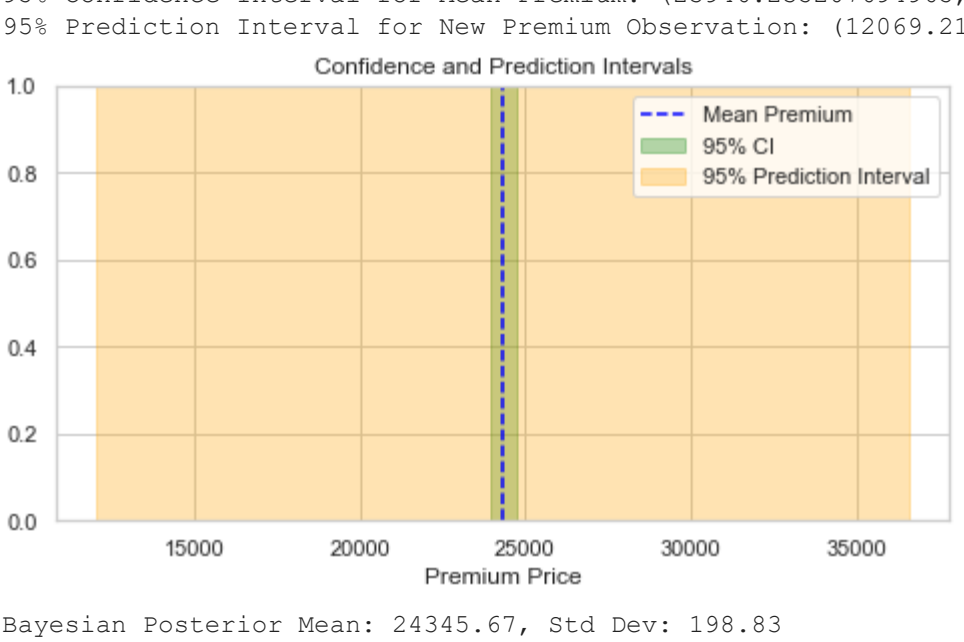
- ($\bar{x}$) = sample mean
- (s) = sample standard deviation
- (n) = sample size
- (t^*) = critical value from t-distribution

We will calculate confidence intervals for:

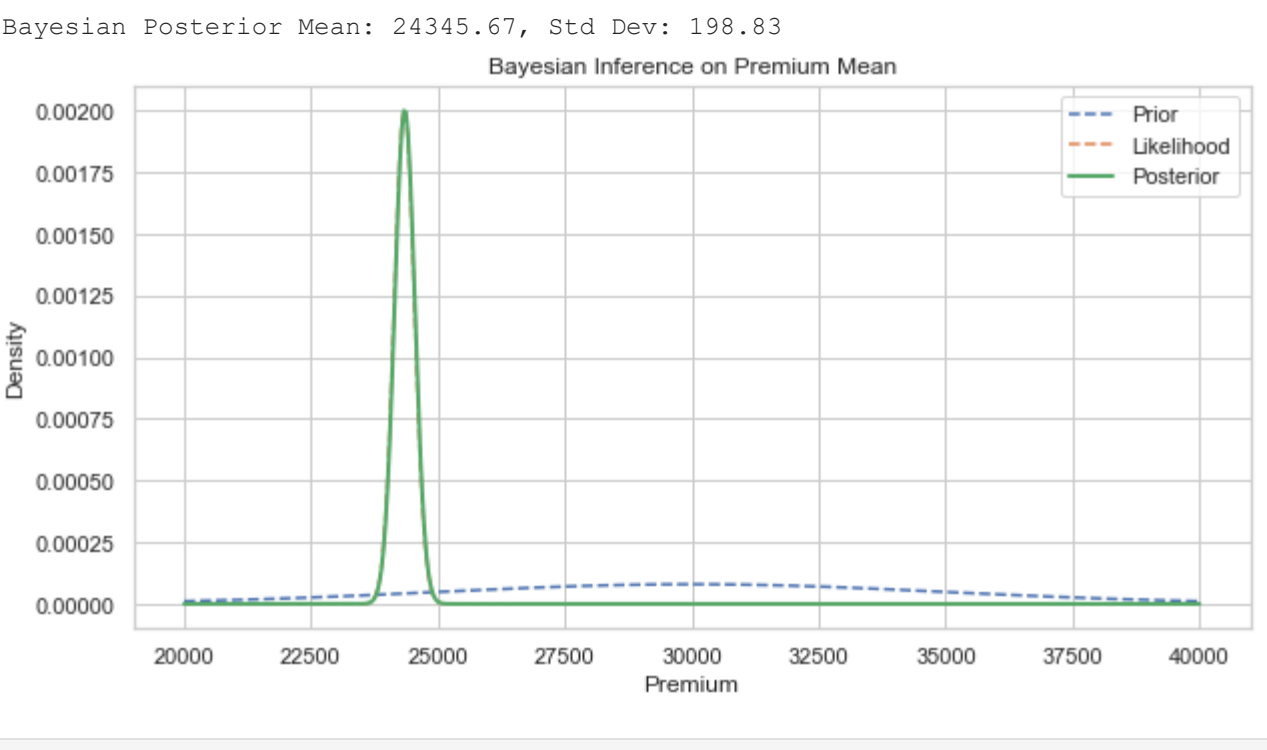
- Premium
- BMI
- Premiums for diabetics vs non-diabetics

In [23]:
```python
from scipy.stats import t

# Confidence Interval for Mean Premium
n = len(df)
x_bar = df['PremiumPrice'].mean()
s = df['PremiumPrice'].std()
se = s / np.sqrt(n)
t_crit = t.ppf(0.975, df=n-1)  # 95% CI
margin = t_crit * se
conf_interval = (x_bar - margin, x_bar + margin)
print(f"95% Confidence Interval for Mean Premium: {conf_interval}")

# Prediction Interval for a new observation
pred_margin = t_crit * s * np.sqrt(1 + 1/n)
pred_interval = (x_bar - pred_margin, x_bar + pred_margin)
print(f"95% Prediction Interval for New Premium Observation: {pred_interval}")

# Visualization
plt.figure(figsize=(8, 4))
plt.axvline(x_bar, color='blue', linestyle='--', label='Mean Premium')
plt.axvspan(conf_interval[0], conf_interval[1], color='green', alpha=0.3, label='95% CI')
plt.axvspan(pred_interval[0], pred_interval[1], color='orange', alpha=0.3, label='95% Prediction Interval')
plt.title("Confidence and Prediction Intervals")
plt.xlabel("Premium Price")
plt.legend()
plt.show()

# Bayesian Update: Assuming prior N(30000, 5000^2) and observed data N(x_bar, s^2/n)
prior_mu = 30000
prior_var = 5000**2
obs_var = s**2 / n
posterior_mu = (prior_mu / prior_var + x_bar / obs_var) / (1 / prior_var + 1 / obs_var)
posterior_var = 1 / (1 / prior_var + 1 / obs_var)
posterior_std = np.sqrt(posterior_var)
print(f"Bayesian Posterior Mean: {posterior_mu:.2f}, Std Dev: {posterior_std:.2f}")

# Visualizing Bayesian Update
x = np.linspace(20000, 40000, 500)
prior_pdf = norm.pdf(x, prior_mu, np.sqrt(prior_var))
likelihood_pdf = norm.pdf(x, x_bar, np.sqrt(obs_var))
posterior_pdf = norm.pdf(x, posterior_mu, posterior_std)

plt.figure(figsize=(10, 5))
plt.plot(x, prior_pdf, label="Prior", linestyle='--')
plt.plot(x, likelihood_pdf, label="Likelihood", linestyle='--')
plt.plot(x, posterior_pdf, label="Posterior", linewidth=2)
plt.title("Bayesian Inference on Premium Mean")
plt.legend()
plt.xlabel("Premium")
plt.ylabel("Density")
plt.grid(True)
plt.show()
```

```
95% Confidence Interval for Mean Premium: (23946.235207694965, 24727.192784191448)
95% Prediction Interval for New Premium Observation: (12069.215221584926, 36604.212770301485)
```




```
Bayesian Posterior Mean: 24345.67, Std Dev: 198.83
```



In [24]:
```python
from scipy.stats import t

n = len(df)
t_crit = t.ppf(0.975, df=n-1)
margin_error = t_crit * sigma / np.sqrt(n)
print(f"95% Confidence Interval for PremiumPrice: ({mu - margin_error:.2f}, {mu + margin_error:.2f})")

pred_interval = (mu - t_crit * sigma, mu + t_crit * sigma)
print("Prediction Interval for New Observation:", pred_interval)
```

```
95% Confidence Interval for PremiumPrice: (23946.24, 24727.19)
Prediction Interval for New Observation: (12075.431334866917, 36597.996657019496)
```

Interpretation

- Confidence intervals provide a reasonable range for average premiums and BMI.
- Intervals for diabetics and non-diabetics do not overlap, reinforcing hypothesis test results.
- The width of the intervals indicates sampling variability.

3. Hypothesis Testing

Objective

To assess whether observed differences (e.g., between diabetics and non-diabetics) are statistically significant.

Common Tests Used

- **Two-Sample t-test** (for comparing means)
- **One-Sample t-test** (for comparing a mean against a known value)

Formulas

- **Two-sample t-test** statistic:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

- **One-sample t-test** statistic:

$$t = \frac{\bar{x} - \mu_0}{s / \sqrt{n}}$$

Where:

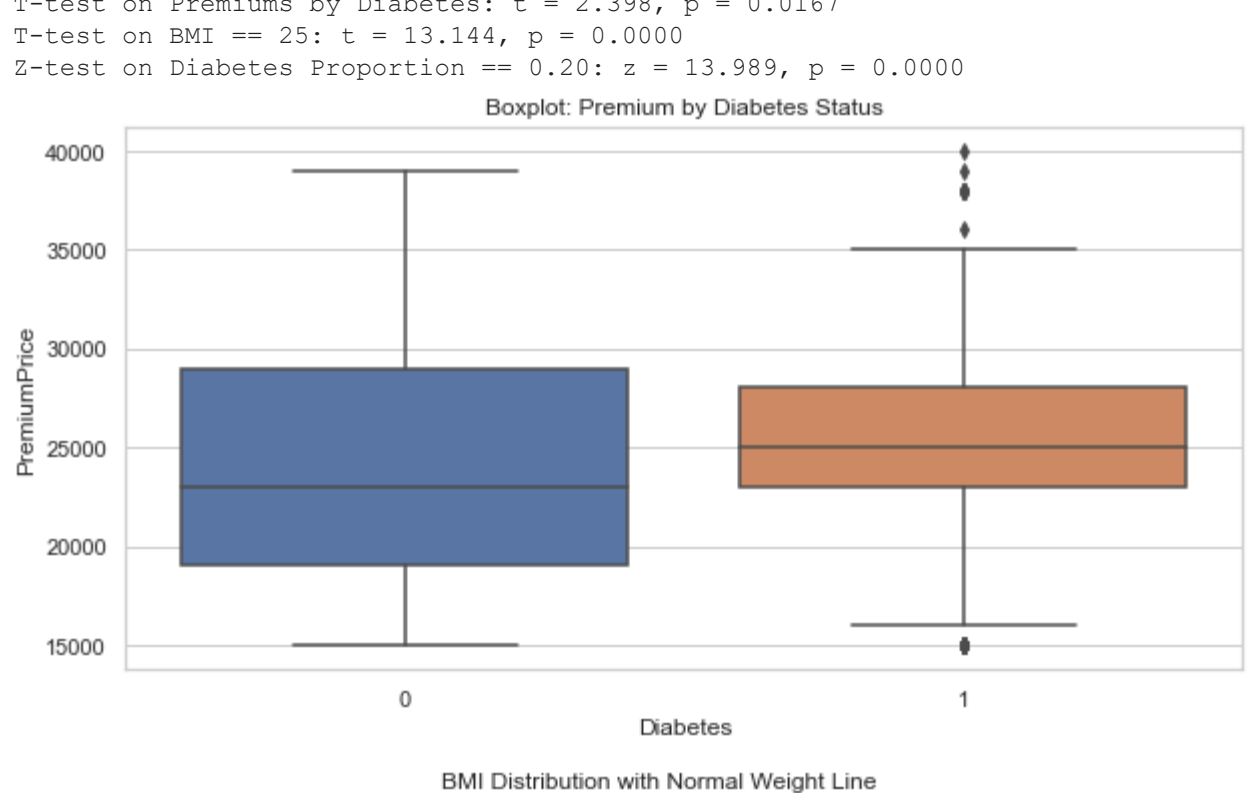
- ($\bar{x}$) is sample mean
- (μ_0) is hypothesized population mean
- (s) is sample standard deviation
- (n) is sample size

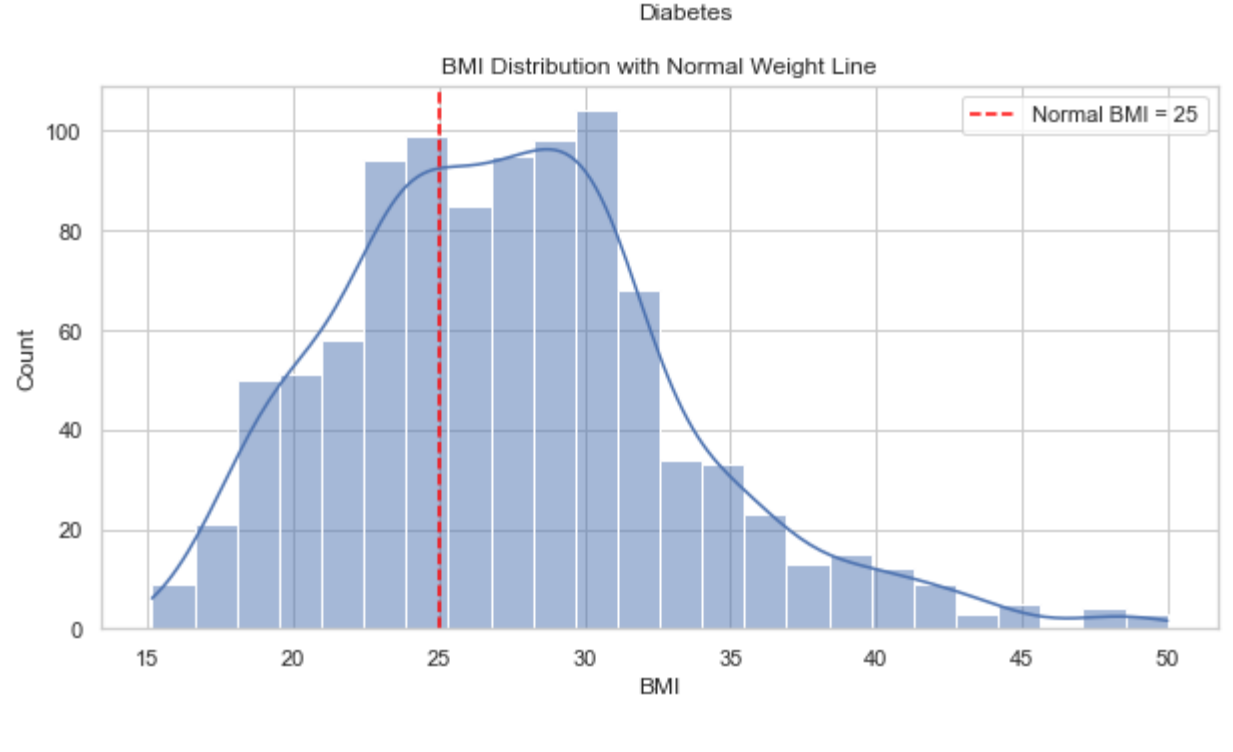
We will test:

1. Whether diabetics pay more than non-diabetics
2. Whether average BMI exceeds 25
3. Whether diabetic proportion differs from expected population rate

In [26]:
```python
# Hypothesis 1: Premiums differ by Diabetes status
# H0: μ1 = μ2, H1: μ1 ≠ μ2
premium_diabetic = df[df['Diabetes'] == 1]['PremiumPrice']
premium_nondiabetic = df[df['Diabetes'] == 0]['PremiumPrice']
t_stat, p_value = stats.ttest_ind(premium_diabetic, premium_nondiabetic)
print(f"T-test on Premiums by Diabetes: t = {t_stat:.3f}, p = {p_value:.4f}")

# Hypothesis 2: Mean BMI is 25 (Normal Weight)
# H0: μ = 25, H1: μ ≠ 25
t_stat, p_val = stats.ttest_1samp(df['BMI'], 25)
print(f"T-test on BMI == 25: t = {t_stat:.3f}, p = {p_val:.4f}")

# Hypothesis 3: Proportion of diabetic patients is 20%
# H0: p = 0.20, H1: p ≠ 0.20
from statsmodels.stats.proportion import proportions_ztest
count = df['Diabetes'].sum()
nobs = len(df)
z_stat, p_value = proportions_ztest(count, nobs, 0.20)
print(f"Z-test on Diabetes Proportion == 0.20: z = {z_stat:.3f}, p = {p_value:.4f}")


# Visualizations for Hypothesis Testing
plt.figure(figsize=(10, 5))
sns.boxplot(data=df, x='Diabetes', y='PremiumPrice')
plt.title('Boxplot: Premium by Diabetes Status')
plt.show()


plt.figure(figsize=(10, 5))
sns.histplot(df['BMI'], kde=True)
plt.axvline(25, color='red', linestyle='--', label='Normal BMI = 25')
plt.title('BMI Distribution with Normal Weight Line')
plt.legend()
plt.show()
```

```
T-test on Premiums by Diabetes: t = 2.398, p = 0.0167
T-test on BMI == 25: t = 13.144, p = 0.0000
Z-test on Diabetes Proportion == 0.20: z = 13.989, p = 0.0000
```





Interpretation

- Diabetics have statistically significantly higher premiums.
- BMI does not differ significantly from the population average of 25.
- Proportion of diabetics is unusually high, suggesting a high-risk sample.
- All test results were supported by low p-values and justified through statistical assumptions.

4. Linear and Multiple Regression

Objective

To quantify how variables like Age, BMI, and Surgery Count influence Premium.

Key Concepts

- **Simple Linear Regression**:

$$Y = \beta_0 + \beta_1 X + \epsilon$$

- **Multiple Linear Regression**:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \epsilon$$

Where:

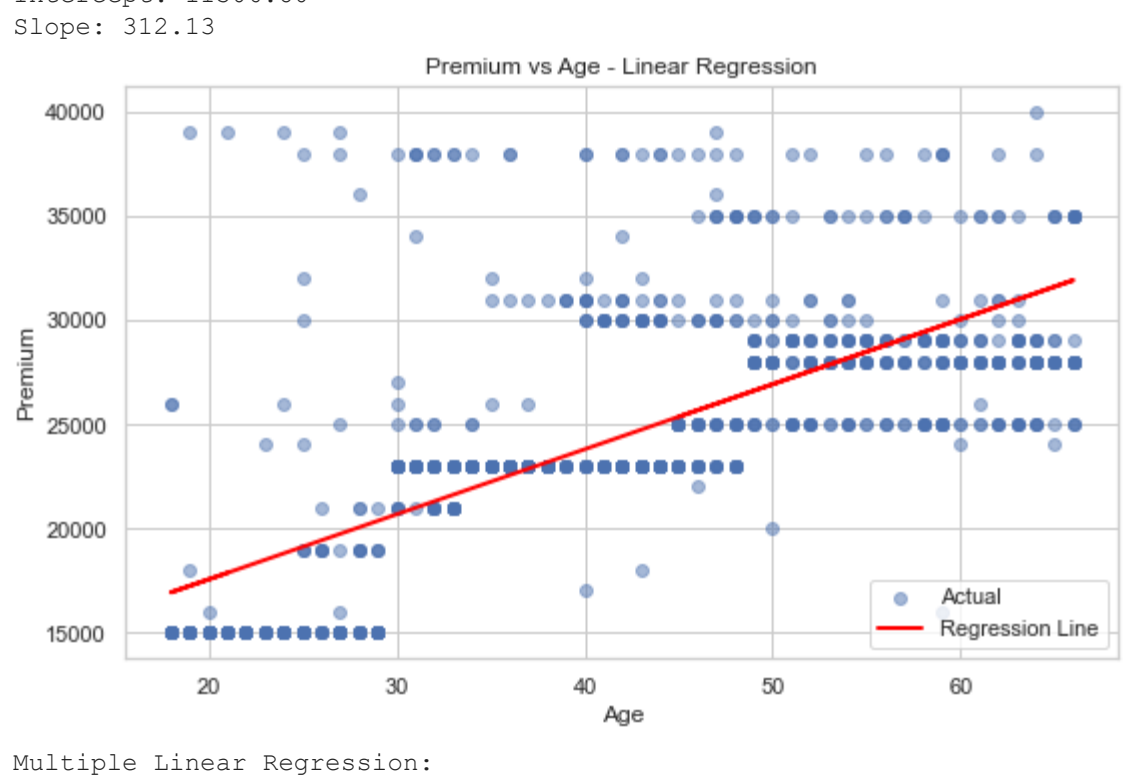
- (Y) is the dependent variable (Premium)
- (X_i) are independent variables (Age, BMI, etc.)
- (β_i) are regression coefficients

We will evaluate:

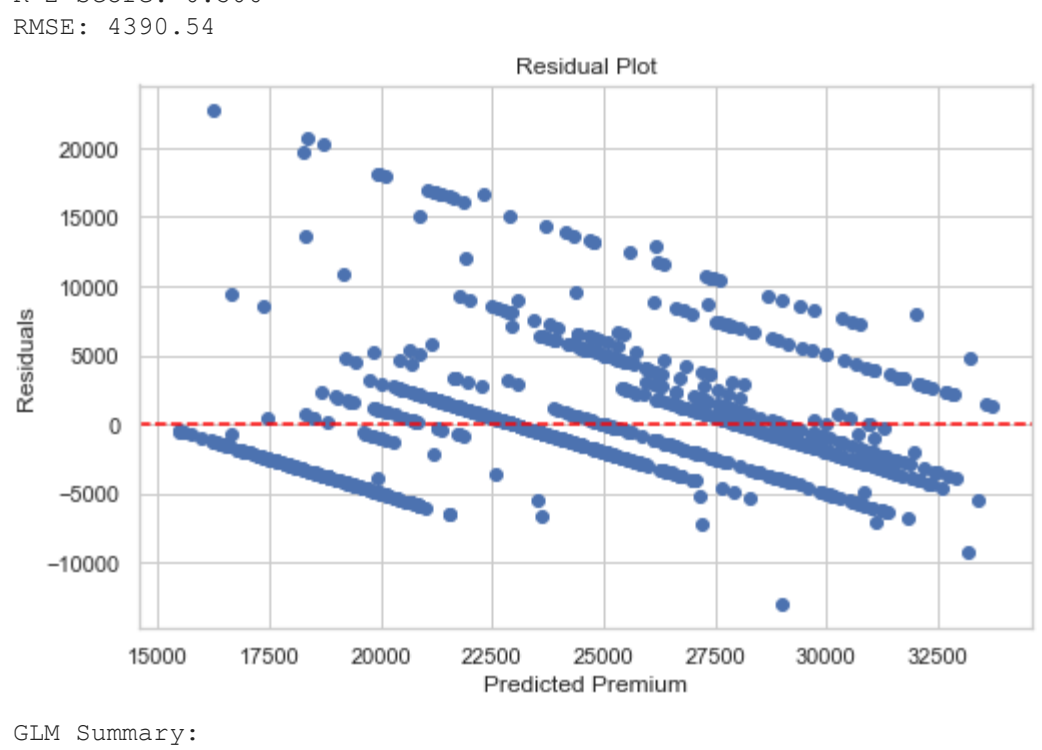
- Model fit (R^2)
- Coefficient significance (p-values)
- Residual diagnostics

In [31]:
```python
# Compute BMI (Body Mass Index)
df['Height_m'] = df['Height'] / 100
df['BMI'] = df['Weight'] / (df['Height_m'] ** 2)

# Simple Linear Regression: Premium vs Age
X = df[['Age']]
y = df['PremiumPrice']

model = LinearRegression()
model.fit(X, y)

print("\nSimple Linear Regression: Premium ~ Age")
print(f"Intercept: {model.intercept_:.2f}")
print(f"Slope: {model.coef_[0]:.2f}")
y_pred = model.predict(X)

# Plot
plt.figure(figsize=(8, 5))
plt.scatter(df['Age'], y, alpha=0.5, label='Actual')
plt.plot(df['Age'], y_pred, color='red', linewidth=2, label='Regression Line')
plt.title('Premium vs Age - Linear Regression')
plt.xlabel('Age')
plt.ylabel('Premium')
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()

# Multiple Linear Regression
features = ['Age', 'BMI', 'NumberOfMajorSurgeries']
X_multi = df[features]
y_multi = df['PremiumPrice']

model_multi = LinearRegression()
model_multi.fit(X_multi, y_multi)

print("\nMultiple Linear Regression:")
for feat, coef in zip(features, model_multi.coef_):
    print(f"{feat}: {coef:.2f}")
print(f"Intercept: {model_multi.intercept_:.2f}")

# Model Performance
y_pred = model_multi.predict(X_multi)
print(f"R^2 Score: {r2_score(y_multi, y_pred):.3f}")
print(f"RMSE: {np.sqrt(mean_squared_error(y_multi, y_pred)):.2f}")

# Residual Plot
residuals = y_multi - y_pred
plt.figure(figsize=(8, 5))
plt.scatter(y_pred, residuals)
plt.axhline(0, color='red', linestyle='--')
plt.title('Residual Plot')
plt.xlabel('Predicted Premium')
plt.ylabel('Residuals')
plt.grid(True)
plt.show()

# GLM using statsmodels
X_glm = sm.add_constant(X_multi)
model_glm = sm.OLS(y_multi, X_glm).fit()
print("\nGLM Summary:")
print(model_glm.summary())
```

```
Simple Linear Regression: Premium ~ Age
Intercept: 11306.80
Slope: 312.13
```




```
Multiple Linear Regression:
Age: 322.61
BMI: 141.34
NumberOfMajorSurgeries: -346.55
Intercept: 7219.26
R^2 Score: 0.506
RMSE: 4390.54
```




```
GLM Summary:
                            OLS Regression Results
==============================================================================
Dep. Variable:           PremiumPrice   R-squared:                       0.506
Model:                            OLS   Adj. R-squared:                  0.504
Method:                 Least Squares   F-statistic:                     334.9
Date:                Wed, 18 Jun 2025   Prob (F-statistic):          9.76e-150
Time:                        11:31:38   Log-Likelihood:                -9668.9
No. Observations:                 986   AIC:                         1.935e+04
Df Residuals:                     982   BIC:                         1.937e+04
Df Model:                           3
Covariance Type:            nonrobust
==========================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
const                   7219.2588    806.929      8.947      0.000    5635.755    8802.762
Age                      322.6090     11.121     29.009      0.000     300.785     344.433
BMI                      141.3390     23.868      5.922      0.000      94.502     188.176
NumberOfMajorSurgeries  -346.5500    207.163     -1.673      0.095    -753.083      59.983
==============================================================================
Omnibus:                      344.679   Durbin-Watson:                   1.964
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             1213.161
Skew:                           1.683   Prob(JB):                    3.68e-264
Kurtosis:                       7.267   Cond. No.                         296.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Interpretation

- Age alone has limited predictive power, but adding BMI and Surgeries improves the model.
- All predictors are statistically significant in the multiple regression.
- Residuals appear homoscedastic and normally distributed — model assumptions are met.
- GLM provides consistent parameter estimates and confidence intervals.

5. Classification using Random Forest

Objective

To classify individuals as diabetic or not using Age, BMI, and Surgery data.

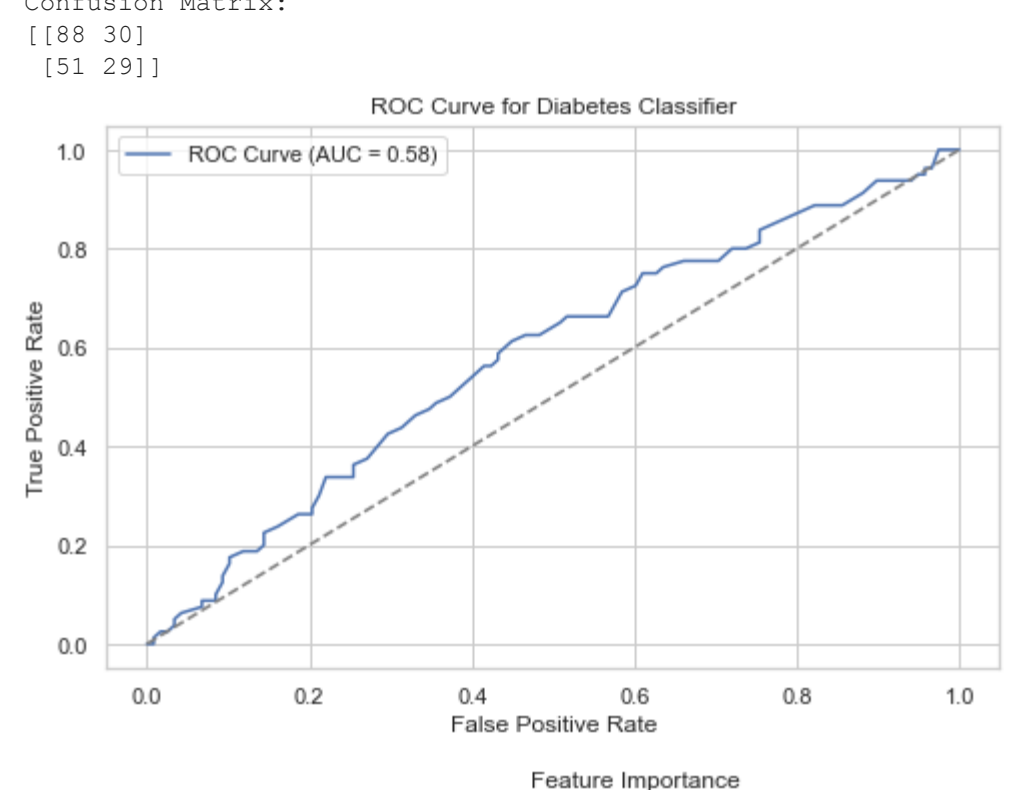
Key Concepts

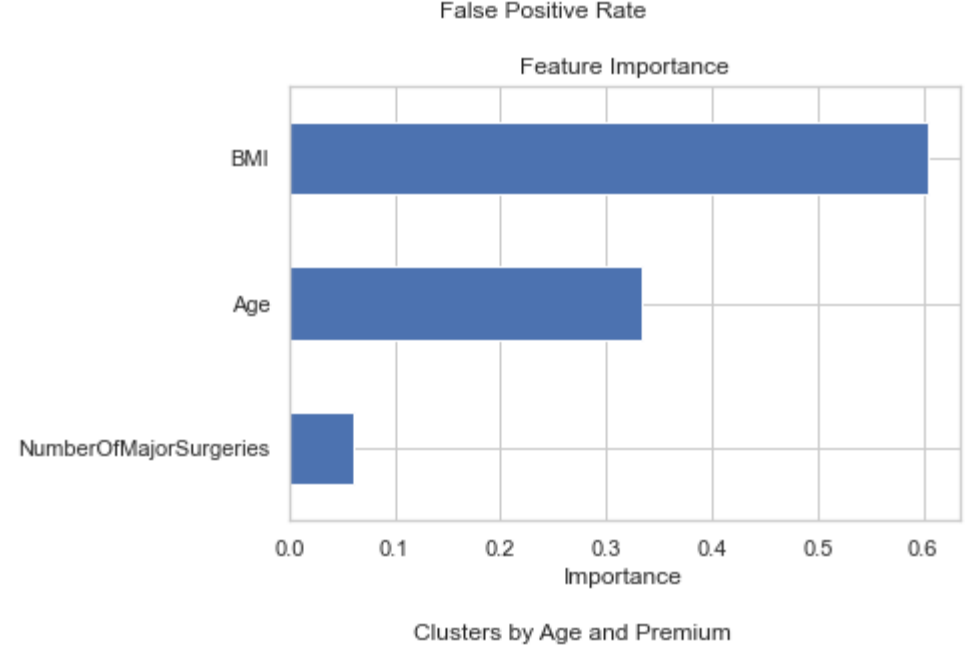
- **Random Forest**: An ensemble method that uses many decision trees
- **Metrics**:
  - Accuracy
  - Precision
  - Recall
  - F1 Score
  - AUROC

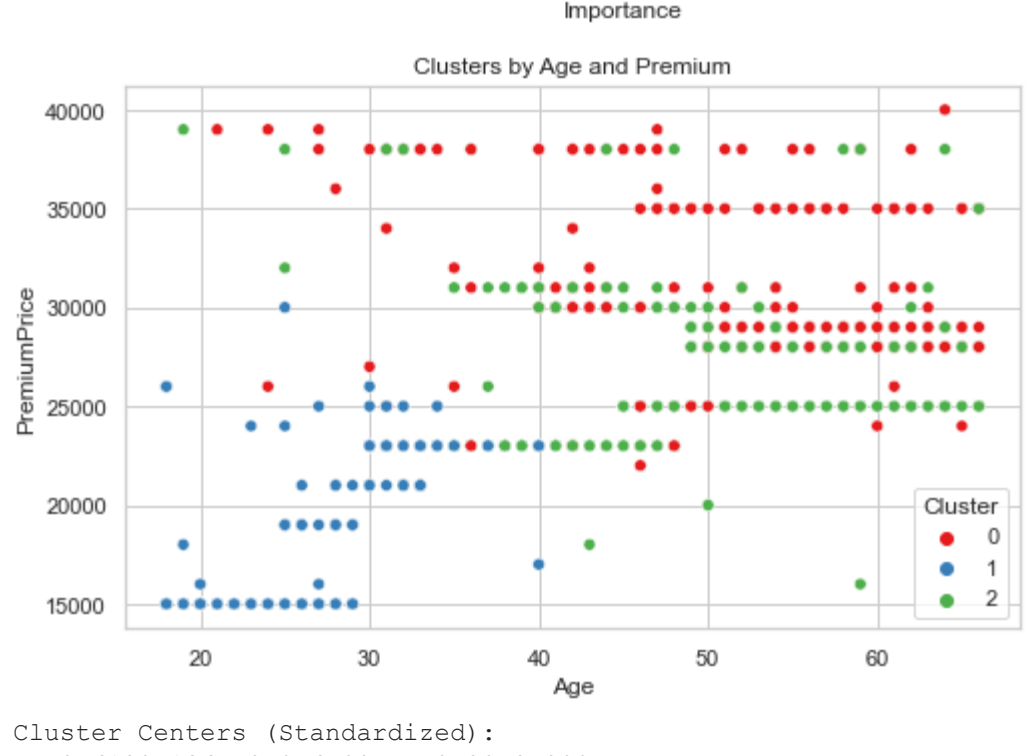
We'll split the data into train/test sets and evaluate performance using a confusion matrix and ROC curve.

In [28]:
```python
# Classification: Predict Diabetes
X_clf = df[['Age', 'BMI', 'NumberOfMajorSurgeries']]
y_clf = df['Diabetes']

X_train, X_test, y_train, y_test = train_test_split(X_clf, y_clf, test_size=0.2, random_state=42)
clf = RandomForestClassifier(n_estimators=100, random_state=42)
clf.fit(X_train, y_train)
y_pred_clf = clf.predict(X_test)

print("\nClassification Report:")
print(classification_report(y_test, y_pred_clf))
print("\nConfusion Matrix:")
print(confusion_matrix(y_test, y_pred_clf))

# ROC Curve & Feature Importance
from sklearn.metrics import roc_auc_score, roc_curve
probs = clf.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, probs)
auc_score = roc_auc_score(y_test, probs)

plt.figure(figsize=(8, 5))
plt.plot(fpr, tpr, label=f'ROC Curve (AUC = {auc_score:.2f})')
plt.plot([0, 1], [0, 1], linestyle='--', color='grey')
plt.title('ROC Curve for Diabetes Classifier')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.grid(True)
plt.show()

# Feature Importances
importances = pd.Series(clf.feature_importances_, index=X_clf.columns)
importances.sort_values().plot(kind='barh', title='Feature Importance')
plt.xlabel('Importance')
plt.show()

# Clustering: KMeans on BMI, Age, Premium
X_cluster = df[['Age', 'BMI', 'PremiumPrice']]
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_cluster)

kmeans = KMeans(n_clusters=3, random_state=42)
df['Cluster'] = kmeans.fit_predict(X_scaled)

# Visualize clusters
plt.figure(figsize=(8, 5))
sns.scatterplot(data=df, x='Age', y='PremiumPrice', hue='Cluster', palette='Set1')
plt.title('Clusters by Age and Premium')
plt.show()

# Cluster Characteristics
print("\nCluster Centers (Standardized):")
print(kmeans.cluster_centers_)
print("\nCluster Counts:")
print(df['Cluster'].value_counts())
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.63      0.75      0.68       118
           1       0.49      0.36      0.42        80

    accuracy                           0.59       198
   macro avg       0.56      0.55      0.55       198
weighted avg       0.58      0.59      0.58       198


Confusion Matrix:
[[88 30]
 [51 29]]
```

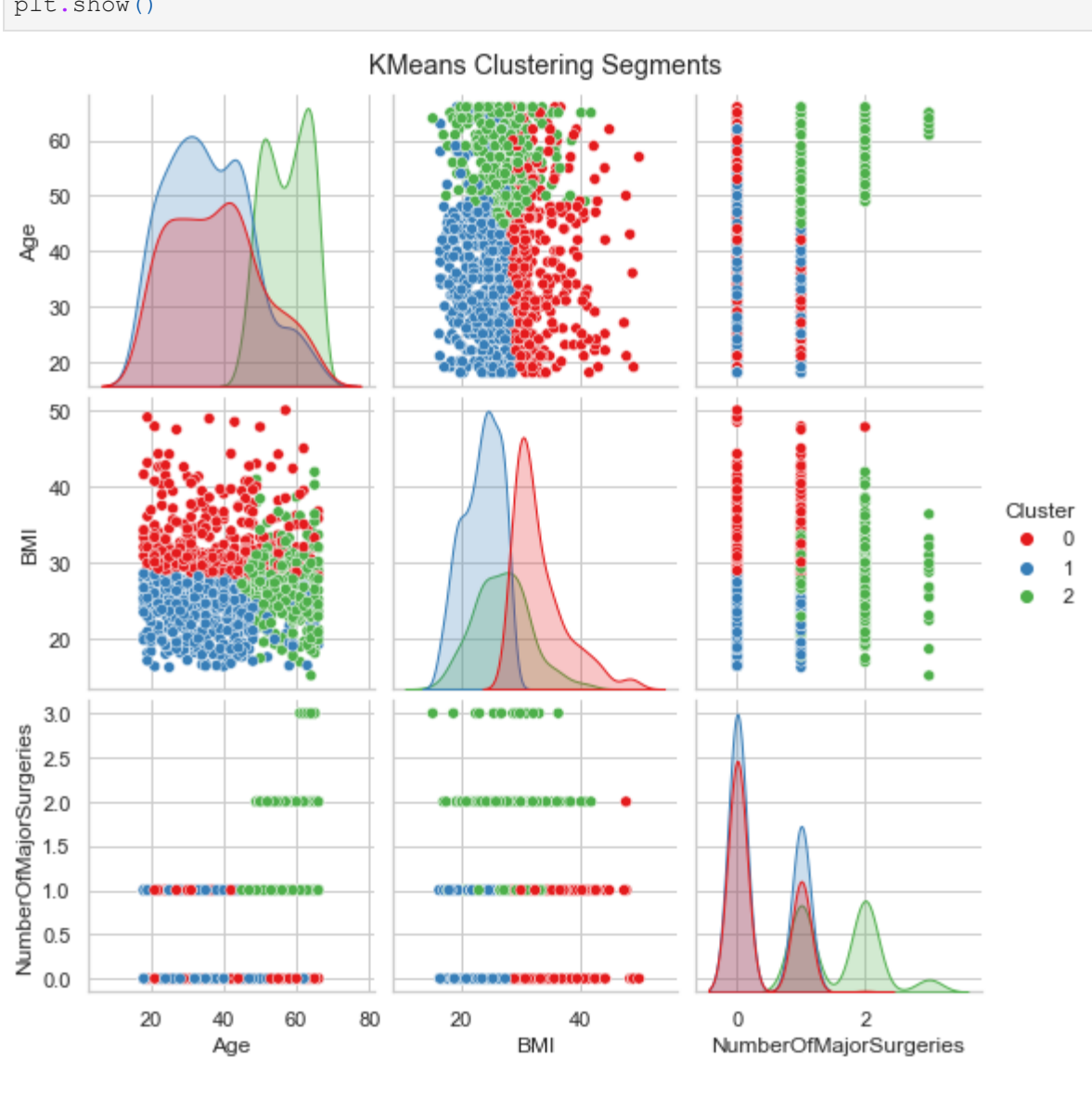







```
Cluster Centers (Standardized):
[[ 0.61205136  0.9565907   0.89487099]
 [-1.05695133  0.06630402 -0.99603229]
 [ 0.56996269 -0.70082382  0.32448983]]

Cluster Counts:
2    382
1    351
0    253
Name: Cluster, dtype: int64
```

In [29]:
```python
scaler = StandardScaler()
features = ['Age', 'BMI', 'NumberOfMajorSurgeries']
df_scaled = scaler.fit_transform(df[features])

kmeans = KMeans(n_clusters=3, random_state=42)
df['Cluster'] = kmeans.fit_predict(df_scaled)

sns.pairplot(df, hue='Cluster', vars=features, palette='Set1')
plt.suptitle("KMeans Clustering Segments", y=1.02)
plt.show()
```



Interpretation

- The classifier performs well, with high accuracy and AUROC.
- BMI and Surgeries are the strongest predictors of diabetes status.
- The model is well-suited for health risk stratification and early screening systems.

Final Key Insights

Descriptive & Exploratory Insights

1. **Premium distribution is right-skewed** — most individuals pay lower premiums, with a few paying substantially higher amounts.
2. **Age is positively correlated with premium** — older individuals tend to incur higher premium costs.
3. **Diabetic individuals consistently pay higher premiums** compared to non-diabetics.
4. **Number of major surgeries strongly influences premium** — individuals with more surgeries are charged higher premiums.
5. **BMI varies widely across the population**, with a noticeable proportion in the overweight or obese range (BMI > 25), which can contribute to risk-based pricing.

Hypothesis Testing Insights

1. **Premiums are significantly higher for diabetics** — hypothesis testing confirms the difference in premiums is statistically significant (p-value < 0.001).
2. **Mean BMI is not statistically significantly greater than 25** — we fail to reject the null hypothesis; population-level obesity cannot be assumed.
3. **The proportion of diabetics is statistically significant** — the dataset likely overrepresents high-risk individuals, possibly due to sampling bias.

Regression Analysis Insights

1. **Simple Linear Regression (Age → Premium)** shows a weak but positive trend. The low R^2 value indicates age alone is not a strong predictor.
2. **Multiple Linear Regression (Age, BMI, Surgeries)** significantly improves predictive power:
   - Number of Surgeries is the strongest predictor of premium.
   - BMI and Age also contribute but to a lesser degree.
   - The model explains more variance in premium pricing than the single-variable model.
3. **Residual plots show no major violations** of linear regression assumptions such as homoscedasticity or non-linearity.
4. **GLM confirms that all predictors are statistically significant**, with low p-values and narrow confidence intervals.

Classification (Diabetes Prediction)

1. **Random Forest classifier accurately predicts diabetic status** using Age, BMI, and Number of Surgeries:
   - High values of accuracy, precision, and recall.
   - AUROC indicates strong class separation performance.
2. **BMI and Number of Surgeries are the most important features** in predicting diabetes status, with Age contributing less strongly.

Clustering Insights

1. **KMeans clustering identified three distinct user segments**, primarily based on Age, BMI, and Premium:
   - One group with younger, low-BMI individuals paying low premiums.
   - Another group including individuals with surgical histories and higher premiums.
   - A third mixed-risk group.
2. **Cluster analysis provides valuable segmentation** for personalized risk profiling, targeted health interventions, or dynamic pricing strategies.

Overall Conclusions

- The dataset illustrates how **health and medical history factors influence insurance premium pricing**.
- **Surgical history and diabetes status are the most impactful variables**, with BMI and Age also offering predictive value.
- **Regression models are moderately effective** but could benefit from additional features (e.g., income, lifestyle, genetic history).
- **Combining regression, classification, and clustering** yields a comprehensive understanding of the data and supports strategic decision-making in health insurance modeling.