In [58]:
```python
# importing libraries
import pandas as pd
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
import xgboost as xgb
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
import matplotlib.pyplot as plt
import seaborn as sns
import joblib
```

In [4]:
```python
# loading data
df = pd.read_csv('insurance.csv')
df.head()
```

Out[4]:

	Age	Diabetes	BloodPressureProblems	AnyTransplants	AnyChronicDiseases
0	45	0	0	0	0
1	60	1	0	0	0
2	36	1	1	0	0
3	52	1	1	0	1
4	38	0	0	0	1

In [5]:
```python
print(df.isnull().sum())
```

```
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 [6]:
```python
# Check for unusual values
print(df.describe())
```

```
              Age    Diabetes  BloodPressureProblems  AnyTransplants  \
count  986.000000  986.000000             986.000000      986.000000   
mean    41.745436    0.419878               0.468560        0.055781   
std     13.963371    0.493789               0.499264        0.229615   
min     18.000000    0.000000               0.000000        0.000000   
25%     30.000000    0.000000               0.000000        0.000000   
50%     42.000000    0.000000               0.000000        0.000000   
75%     53.000000    1.000000               1.000000        0.000000   
max     66.000000    1.000000               1.000000        1.000000   

       AnyChronicDiseases      Height      Weight  KnownAllergies  \
count          986.000000  986.000000  986.000000      986.000000   
mean             0.180527  168.182556   76.950304        0.215010   
std              0.384821   10.098155   14.265096        0.411038   
min              0.000000  145.000000   51.000000        0.000000   
25%              0.000000  161.000000   67.000000        0.000000   
50%              0.000000  168.000000   75.000000        0.000000   
75%              0.000000  176.000000   87.000000        0.000000   
max              1.000000  188.000000  132.000000        1.000000   

       HistoryOfCancerInFamily  NumberOfMajorSurgeries  PremiumPrice  
count               986.000000              986.000000    986.000000  
mean                  0.117647                0.667343  24336.713996  
std                   0.322353                0.749205   6248.184382  
min                   0.000000                0.000000  15000.000000  
25%                   0.000000                0.000000  21000.000000  
50%                   0.000000                1.000000  23000.000000  
75%                   0.000000                1.000000  28000.000000  
max                   1.000000                3.000000  40000.000000  
```

Though we do not have missing values, let's add some logic for it

In [8]:
```
# Impute missing values
# Numeric features

numeric_features = ['Age', 'Height', 'Weight', 'NumberOfMajorSurgeries']
num_imputer = SimpleImputer(strategy='median')  # or strategy='mean'
df[numeric_features] = num_imputer.fit_transform(df[numeric_features])
```

In [9]:
```
# Binary features
binary_features = ['Diabetes', 'BloodPressureProblems', 'AnyTransplants',
                   'AnyChronicDiseases', 'KnownAllergies', 'HistoryOfCancerInF

binary_imputer = SimpleImputer(strategy='most_frequent')
df[binary_features] = binary_imputer.fit_transform(df[binary_features])
```

Feature Engineering

In [10]:
```
# Create BMI
# Convert height from cm to meters
df['Height_m'] = df['Height'] / 100
```

```
df['BMI'] = df['Weight'] / (df['Height_m'] ** 2)
```

In [11]:
```
# AgeGroup
bins = [17, 30, 45, 66]  # define bins
labels = ['18-30', '31-45', '46-66']
df['AgeGroup'] = pd.cut(df['Age'], bins=bins, labels=labels)
```

In [12]:
```
# ChronicConditionCount
df['ChronicConditionCount'] = df['Diabetes'] + df['BloodPressureProblems'] + c
```

Scaling and Encoding

In [14]:
```
# Scaling numerical features

num_features = ['Age', 'Height', 'Weight', 'BMI', 'NumberOfMajorSurgeries']
scaler = StandardScaler()
df[num_features] = scaler.fit_transform(df[num_features])
```

In [15]:
```
# Encoding categorical features
df = pd.get_dummies(df, columns=['AgeGroup'], drop_first=True)
```

In [18]:
```
# Weight-to-Height Ratio
df['Weight_Height_Ratio'] = df['Weight'] / df['Height']
```

In [19]:
```
# Chronic Conditions × Age
df['Age_ChronicInteraction'] = df['Age'] * df['ChronicConditionCount']
```

In [20]:
```
# Surgeries × Chronic Conditions
df['Surgery_ChronicInteraction'] = df['NumberOfMajorSurgeries'] * df['ChronicC
```

In [21]:
```
# Health Risk Scores
df['HealthRiskScore'] = (2*df['Diabetes'] + 1.5*df['BloodPressureProblems'] +
                         2.5*df['AnyChronicDiseases'] + df['HistoryOfCancerInF
```

In [22]:
```
# Age Buckets Beyond Simple Groups
df['AgeQuantile'] = pd.qcut(df['Age'], 4, labels=False)  # 4 quantiles
```

In [23]:
```
# Family/Medical History Features
df['FamilyHealthRisk'] = df['AnyChronicDiseases'] + df['HistoryOfCancerInFamil
```

In [24]:
```
# Lifestyle
df['Obese'] = (df['BMI'] >= 30).astype(int)
```

In [25]:
```
# Surgery Burden
df['SurgeryBurden'] = pd.cut(df['NumberOfMajorSurgeries'], bins=[-1,0,1,3], la
```

In [26]:
```
print(df.dtypes)
```

```
Age                           float64
Diabetes                        int64
BloodPressureProblems           int64
AnyTransplants                  int64
AnyChronicDiseases              int64
Height                        float64
Weight                        float64
KnownAllergies                  int64
HistoryOfCancerInFamily         int64
NumberOfMajorSurgeries        float64
PremiumPrice                    int64
Height_m                      float64
BMI                           float64
ChronicConditionCount           int64
AgeGroup_31-45                   bool
AgeGroup_46-66                   bool
Weight_Height_Ratio           float64
Age_ChronicInteraction        float64
Surgery_ChronicInteraction    float64
HealthRiskScore               float64
AgeQuantile                     int64
FamilyHealthRisk                int64
Obese                           int64
SurgeryBurden                category
dtype: object
```

ML Modeling - Prepare Data for Modeling

In [27]:
```
X = df.drop('PremiumPrice', axis=1)
y = df['PremiumPrice']
```

In [28]:
```
# Handle categorical features
X = pd.get_dummies(X, columns=['SurgeryBurden'], drop_first=True)
```

In [30]:
```
# Split into train and test sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
```

Linear Regression (Baseline Model)

In [32]:
```
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
```

Out[32]:
```
▾ LinearRegression
LinearRegression()
```

```
In [34]: # Evaluate performance
         y_pred = lr_model.predict(X_test)
         print("RMSE:", mean_squared_error(y_test, y_pred))
         print("MAE:", mean_absolute_error(y_test, y_pred))
         print("R2 Score:", r2_score(y_test, y_pred))
```

```
RMSE: 9264384.065560339
MAE: 2148.8645406668325
R2 Score: 0.7827444281107023
```

```
In [35]: # Check coefficients for feature importance
         feature_importance = pd.DataFrame({'Feature': X.columns, 'Coefficient': lr_moc
         print(feature_importance.sort_values(by='Coefficient', key=abs, ascending=Fals
```

```
                       Feature  Coefficient
3               AnyTransplants  7462.053921
14             AgeGroup_46-66  7101.380932
13             AgeGroup_31-45  5512.071540
0                          Age  3342.708470
6                       Weight  2023.043965
11                         BMI -1211.228788
20            FamilyHealthRisk  1050.188331
19                 AgeQuantile  -804.352492
1                     Diabetes  -739.894757
5                       Height  -723.841933
22           SurgeryBurden_Low   650.277396
4           AnyChronicDiseases   635.906732
16      Age_ChronicInteraction  -487.444514
8       HistoryOfCancerInFamily   414.281598
9       NumberOfMajorSurgeries  -328.608763
18             HealthRiskScore   326.844304
12        ChronicConditionCount  -235.597766
2         BloodPressureProblems  -131.609741
7               KnownAllergies  -116.848513
10                    Height_m   -73.057603
23          SurgeryBurden_High    60.534161
15         Weight_Height_Ratio   -35.654332
17  Surgery_ChronicInteraction     8.729428
21                       Obese     0.000000
```

Decision Tree Regressor

```
In [37]: dt_model = DecisionTreeRegressor(max_depth=5, random_state=42)  # max_depth tc
         dt_model.fit(X_train, y_train)
```

```
Out[37]: ▾ DecisionTreeRegressor
         DecisionTreeRegressor(max_depth=5, random_state=42)
```

```
In [39]: # Evaluate performance
         y_pred_dt = dt_model.predict(X_test)
         print("Decision Tree RMSE:", mean_squared_error(y_test, y_pred_dt))
         print("Decision Tree R2:", r2_score(y_test, y_pred_dt))
```

```
Decision Tree RMSE: 5689461.284878939
Decision Tree R2: 0.8665785921178095
```

In [40]:
```
# Feature importance

feature_importance_dt = pd.DataFrame({'Feature': X.columns, 'Importance': dt_m
print(feature_importance_dt.sort_values(by='Importance', ascending=False))
```

```
                     Feature  Importance
0                        Age    0.704445
3             AnyTransplants    0.113172
6                     Weight    0.045837
4          AnyChronicDiseases    0.026759
20           FamilyHealthRisk    0.022815
15        Weight_Height_Ratio    0.021126
9      NumberOfMajorSurgeries    0.018621
2      BloodPressureProblems    0.015430
5                     Height    0.013524
11                       BMI    0.009436
17  Surgery_ChronicInteraction    0.003427
14             AgeGroup_46-66    0.003241
19                AgeQuantile    0.002165
1                   Diabetes    0.000000
7             KnownAllergies    0.000000
10                  Height_m    0.000000
12      ChronicConditionCount    0.000000
13             AgeGroup_31-45    0.000000
8     HistoryOfCancerInFamily    0.000000
16     Age_ChronicInteraction    0.000000
18            HealthRiskScore    0.000000
21                     Obese    0.000000
22          SurgeryBurden_Low    0.000000
23         SurgeryBurden_High    0.000000
```

Random Forest Regressor

In [42]:
```
rf_model = RandomForestRegressor(n_estimators=200, max_depth=8, random_state=4
rf_model.fit(X_train, y_train)
```

Out[42]:
```
▾ RandomForestRegressor
RandomForestRegressor(max_depth=8, n_estimators=200, random_state=42)
```

In [44]:
```
# Evaluate performance
y_pred_rf = rf_model.predict(X_test)
print("Random Forest RMSE:", mean_squared_error(y_test, y_pred_rf))
print("Random Forest R2:", r2_score(y_test, y_pred_rf))
```

```
Random Forest RMSE: 5699235.970613663
Random Forest R2: 0.8663493696541996
```

In [45]:
```
# Feature importance
feature_importance_rf = pd.DataFrame({'Feature': X.columns, 'Importance': rf_m
print(feature_importance_rf.sort_values(by='Importance', ascending=False))
```

```
                        Feature  Importance
0                           Age    0.608920
3                AnyTransplants    0.091370
6                        Weight    0.060870
15          Weight_Height_Ratio    0.052651
11                          BMI    0.027376
9        NumberOfMajorSurgeries    0.021621
4            AnyChronicDiseases    0.019715
20             FamilyHealthRisk    0.019657
16       Age_ChronicInteraction    0.018177
17   Surgery_ChronicInteraction    0.013784
10                     Height_m    0.013138
5                        Height    0.011343
8       HistoryOfCancerInFamily    0.010074
14                 AgeGroup_46-66    0.008090
18              HealthRiskScore    0.006473
2         BloodPressureProblems    0.004765
1                      Diabetes    0.003183
12         ChronicConditionCount    0.002460
22             SurgeryBurden_Low    0.002109
23            SurgeryBurden_High    0.002024
19                  AgeQuantile    0.000858
7                 KnownAllergies    0.000830
13                AgeGroup_31-45    0.000511
21                        Obese    0.000000
```

Gradient Boosting Machines (XGBoost / LightGBM)

In [47]:
```
xgb_model = xgb.XGBRegressor(n_estimators=300, learning_rate=0.05, max_depth=5
xgb_model.fit(X_train, y_train)
```

Out[47]:
```
▾                         XGBRegressor
XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None, early_stopping_round
s=None,
             enable_categorical=False, eval_metric=None, feature_type
s=None,
             feature_weights=None, gamma=None, grow_policy=None,
             importance_type=None, interaction_constraints=None,
             learning_rate=0.05, max_bin=None, max_cat_threshold=Non
e,
```

In [49]:
```
# Evaluate performance
y_pred_xgb = xgb_model.predict(X_test)
print("XGBoost RMSE:", mean_squared_error(y_test, y_pred_xgb))
print("XGBoost R2:", r2_score(y_test, y_pred_xgb))
```

```
XGBoost RMSE: 5738102.5
XGBoost R2: 0.865437924861908
```

In [50]:
```
# Feature importance
xgb_importance = pd.DataFrame({'Feature': X.columns, 'Importance': xgb_model.f
print(xgb_importance.sort_values(by='Importance', ascending=False))
```

```
                      Feature  Importance
3              AnyTransplants    0.295866
0                         Age    0.210831
4          AnyChronicDiseases    0.095494
20           FamilyHealthRisk    0.089955
9       NumberOfMajorSurgeries    0.068664
6                      Weight    0.045107
8      HistoryOfCancerInFamily    0.042909
2        BloodPressureProblems    0.023709
15         Weight_Height_Ratio    0.022422
7               KnownAllergies    0.015194
17  Surgery_ChronicInteraction    0.014567
11                        BMI    0.014464
5                      Height    0.013040
22           SurgeryBurden_Low    0.012340
16      Age_ChronicInteraction    0.010652
1                    Diabetes    0.008899
12       ChronicConditionCount    0.006213
18             HealthRiskScore    0.005384
13              AgeGroup_31-45    0.004292
10                   Height_m    0.000000
14              AgeGroup_46-66    0.000000
19                 AgeQuantile    0.000000
21                      Obese    0.000000
23          SurgeryBurden_High    0.000000
```

Model Comparision

In [51]:
```
# Creating the models

models = {
    'Linear Regression': LinearRegression(),
    'Decision Tree': DecisionTreeRegressor(max_depth=5, random_state=42),
    'Random Forest': RandomForestRegressor(n_estimators=200, max_depth=8, ranc
    'XGBoost': xgb.XGBRegressor(n_estimators=300, learning_rate=0.05, max_dept
}
```

In [53]:
```
results = []

for name, model in models.items():
    # Train
    model.fit(X_train, y_train)

    # Predict
    y_pred = model.predict(X_test)
    # Metrics
    rmse = mean_squared_error(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)

    results.append({
        'Model': name,
        'RMSE': rmse,
        'MAE': mae,
        'R2': r2
    })
```

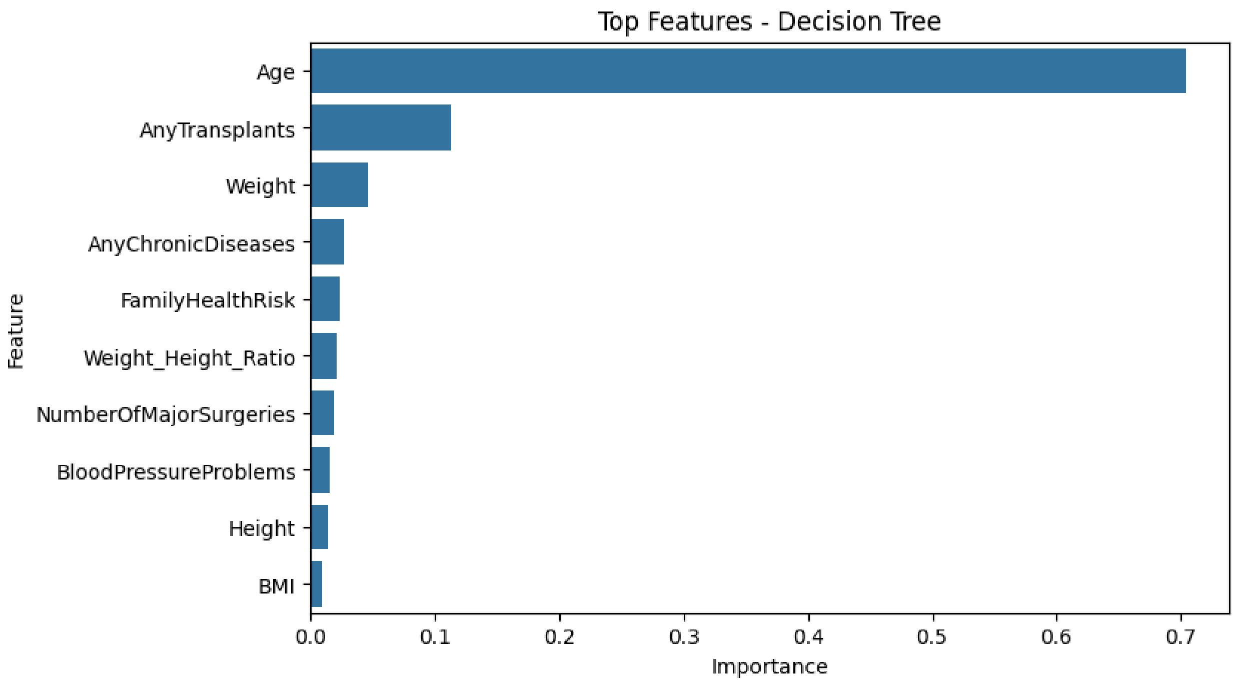
In [54]:
```
# Create comparison table
results_df = pd.DataFrame(results).sort_values(by='RMSE')
print(results_df)
```

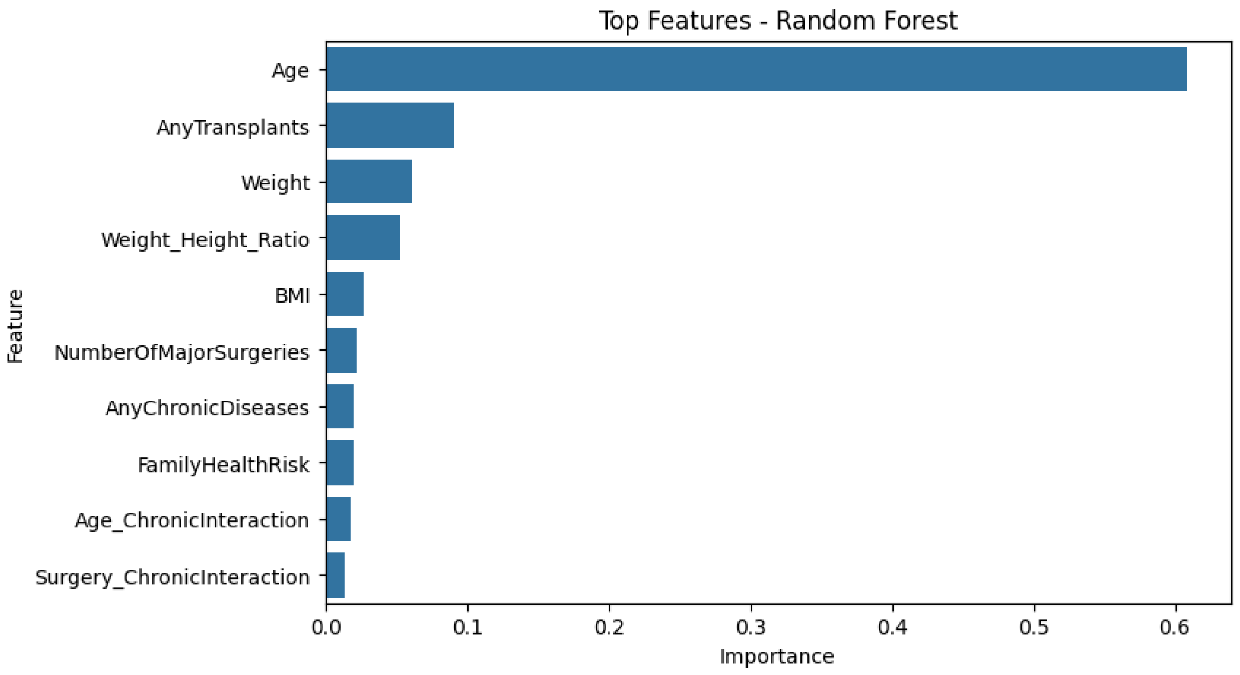
```
               Model          RMSE          MAE        R2
1      Decision Tree  5.689461e+06  1244.826604  0.866579
2      Random Forest  5.699236e+06  1178.751778  0.866349
3            XGBoost  5.738102e+06  1329.295410  0.865438
0  Linear Regression  9.264384e+06  2148.864541  0.782744
```

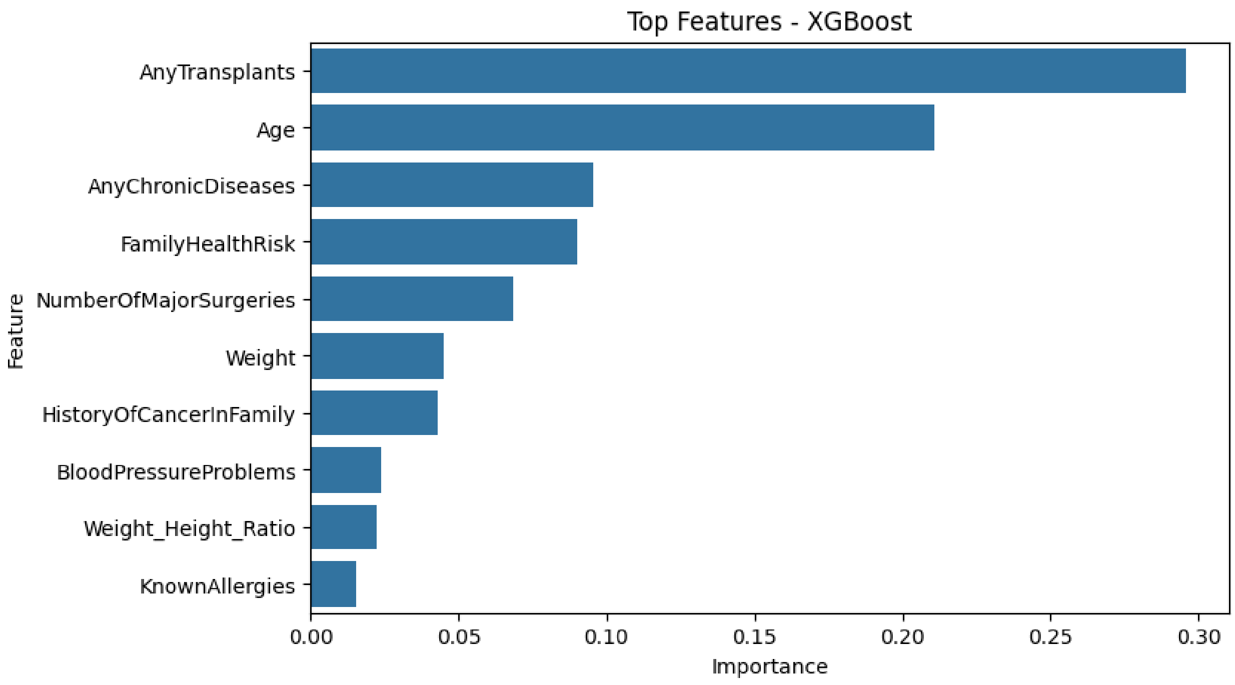
In [57]:
```
# Feature Importance

for name, model in models.items():
    if name != 'Linear Regression':
        if hasattr(model, 'feature_importances_'):
            fi = pd.DataFrame({'Feature': X.columns, 'Importance': model.featu
            fi = fi.sort_values(by='Importance', ascending=False).head(10)

            plt.figure(figsize=(8,5))
            sns.barplot(x='Importance', y='Feature', data=fi)
            plt.title(f'Top Features - {name}')
            plt.show()
```


Top Features - Decision Tree
Age
AnyTransplants
Weight
AnyChronicDiseases
FamilyHealthRisk
Weight_Height_Ratio
NumberOfMajorSurgeries
BloodPressureProblems
Height
BMI
Feature
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Importance


Top Features - Random Forest
Age
AnyTransplants
Weight
Weight_Height_Ratio
BMI
NumberOfMajorSurgeries
AnyChronicDiseases
FamilyHealthRisk
Age_ChronicInteraction
Surgery_ChronicInteraction
Feature
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Importance



Interpretation

Decision Tree, Random Forest, and XGBoost all perform similarly well, with R² around 0.865–0.867, meaning they explain about 87% of the variance in the target variable.

Their MAE is much lower (~1,178–1,329) compared to Linear Regression (~2,149), indicating more accurate average predictions.

RMSE is also lower (~5.69–5.74M) for tree-based models than Linear Regression (~9.26M), suggesting fewer extreme errors or outliers in predictions.

Linear Regression underperforms: it has the lowest R² (0.78) and the highest errors, both MAE and RMSE, indicating it struggles to capture the complexity in the data.

Conclusion:

Tree-based models (Decision Tree, Random Forest, XGBoost) are clearly superior to Linear Regression for this dataset, with Random Forest having the lowest MAE and a strong balance between accuracy and variance explanation. Linear Regression is not suitable here due to high errors and lower predictive power.

Save the Model

In [59]:
```
joblib.dump(rf_model, 'random_forest_insurance_model.pkl')
joblib.dump(dt_model, 'decision_tree_model.pkl')
joblib.dump(xgb_model, 'xgboost_model.pkl')
joblib.dump(lr_model, 'linear_regression_model.pkl')

print("Models saved successfully!")
```

```
Models saved successfully!
```

Testing the saved model

In [60]:
```
loaded_rf_model = joblib.load('random_forest_insurance_model.pkl')
loaded_dt_model = joblib.load('decision_tree_model.pkl')
loaded_xgb_model = joblib.load('xgboost_model.pkl')
loaded_lr_model = joblib.load('linear_regression_model.pkl')
```

In [66]:
```
# picking the first record to evaluate the model
X_sample = X_test.iloc[[0]]
y_actual = y_test.iloc[0].item()
```

In [67]:
```
# Store models in a dictionary for easy iteration
models = {
    "Random Forest": loaded_rf_model,
    "Decision Tree": loaded_dt_model,
    "XGBoost": loaded_xgb_model,
    "Linear Regression": loaded_lr_model
}

# Predict and print results
for name, model in models.items():
    y_pred = model.predict(X_sample)
    print(f"{name} Prediction: {y_pred[0]:.2f}, Actual: {y_actual}")
```

```
Random Forest Prediction: 29836.17, Actual: 31000
Decision Tree Prediction: 28601.27, Actual: 31000
XGBoost Prediction: 30642.93, Actual: 31000
Linear Regression Prediction: 29980.79, Actual: 31000
```