Machine Learning Model For Insurance Premium Prediction

Project Objective:

Accurately predict health insurance premiums for individuals using machine learning.

Enable insurers to offer fair, personalized pricing while managing risk effectively.

Identify key health and demographic factors that influence insurance costs.

Goals:

Prepare data: handle missing values, outliers.

Feature engineering: BMI, AgeGroup, ChronicConditionCount, interactions, HealthRiskScore.

Scale numeric features, encode categorical/binary features.

Model Selection:

Linear Regression: baseline, interpretable.

Tree-based models: Decision Tree, Random Forest, Gradient Boosting for non-linear relationships.

Evaluation:

Cross-validation (k-fold) for robust performance.

Metrics: RMSE, MAE, R^2.

Optional: prediction intervals for reliability.

Interpretability:

Feature importance (tree-based or SHAP).

Identify key risk factors affecting premiums.

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]:
```python
# 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]:
```python
# 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]:
```python
# 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, randc
```

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]:
```python
# 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]:
```python
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]:
```python
# 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]:
```python
# 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
    })
```

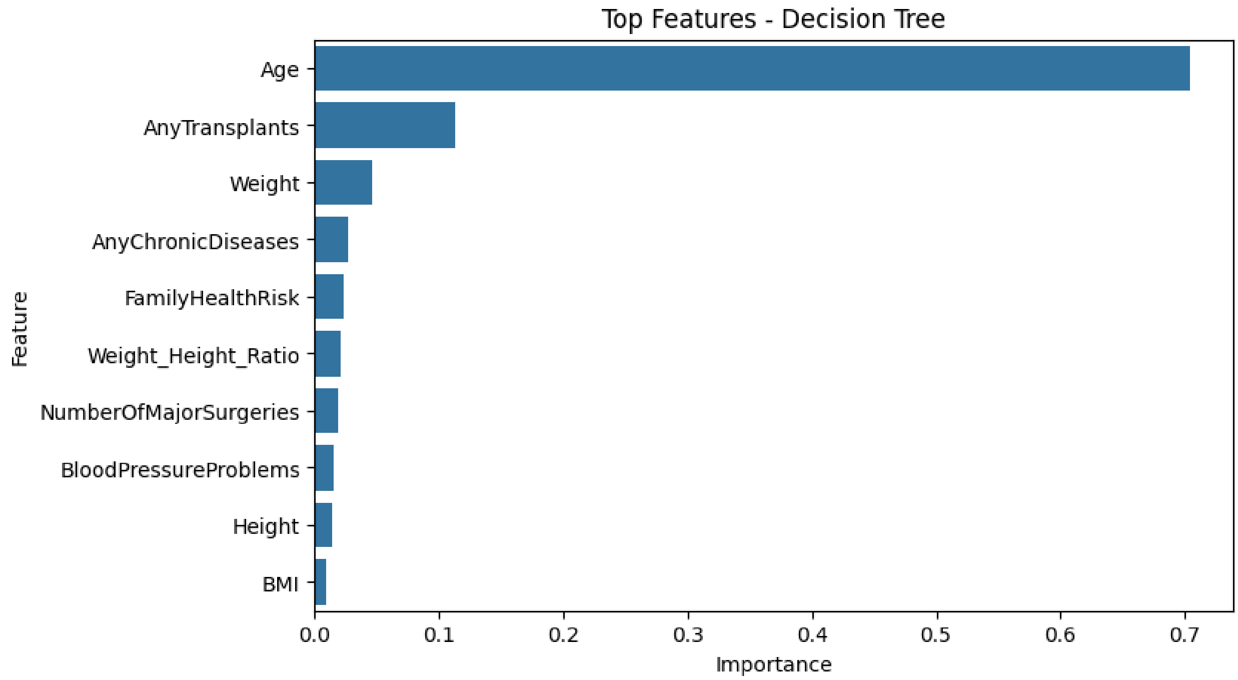
In [54]:
```
# Create comparison table
results_df = pd.DataFrame(results).sort_values(by='RMSE')
print(results_df)
```

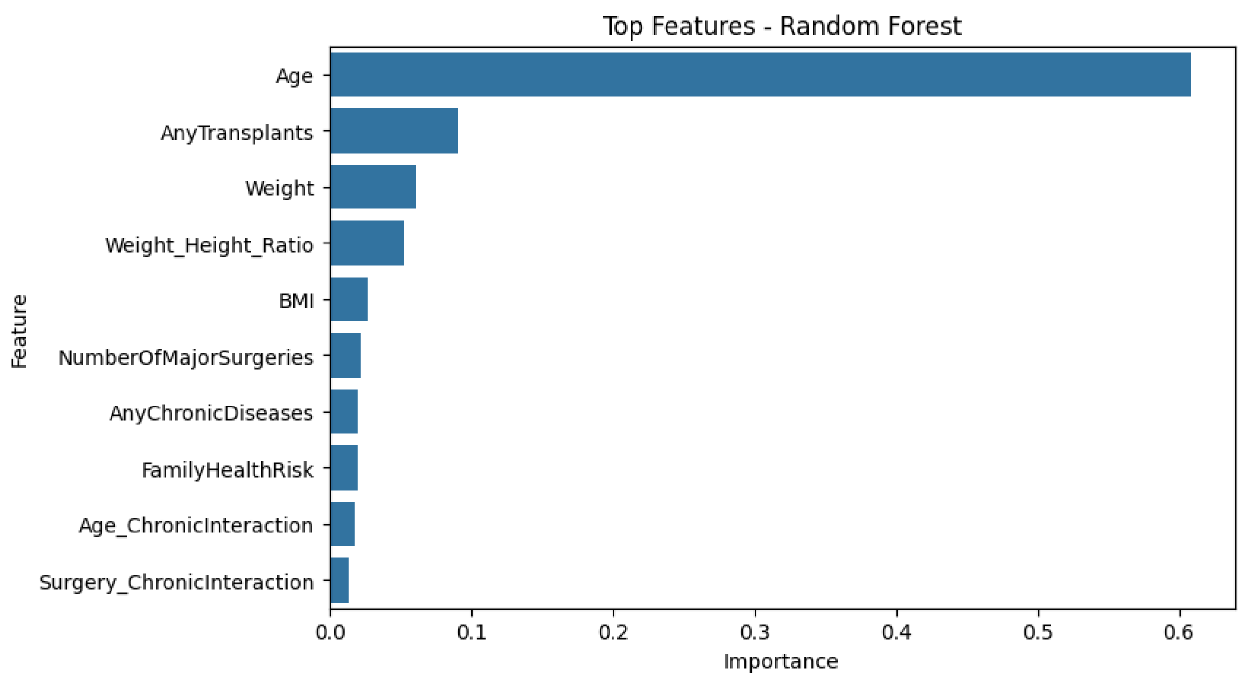
```
               Model          RMSE          MAE        R2
1      Decision Tree  5.689461e+06  1244.826604  0.866579
2      Random Forest  5.699236e+06  1178.751778  0.866349
3            XGBoost  5.738102e+06  1329.295410  0.865438
0  Linear Regression  9.264384e+06  2148.864541  0.782744
```

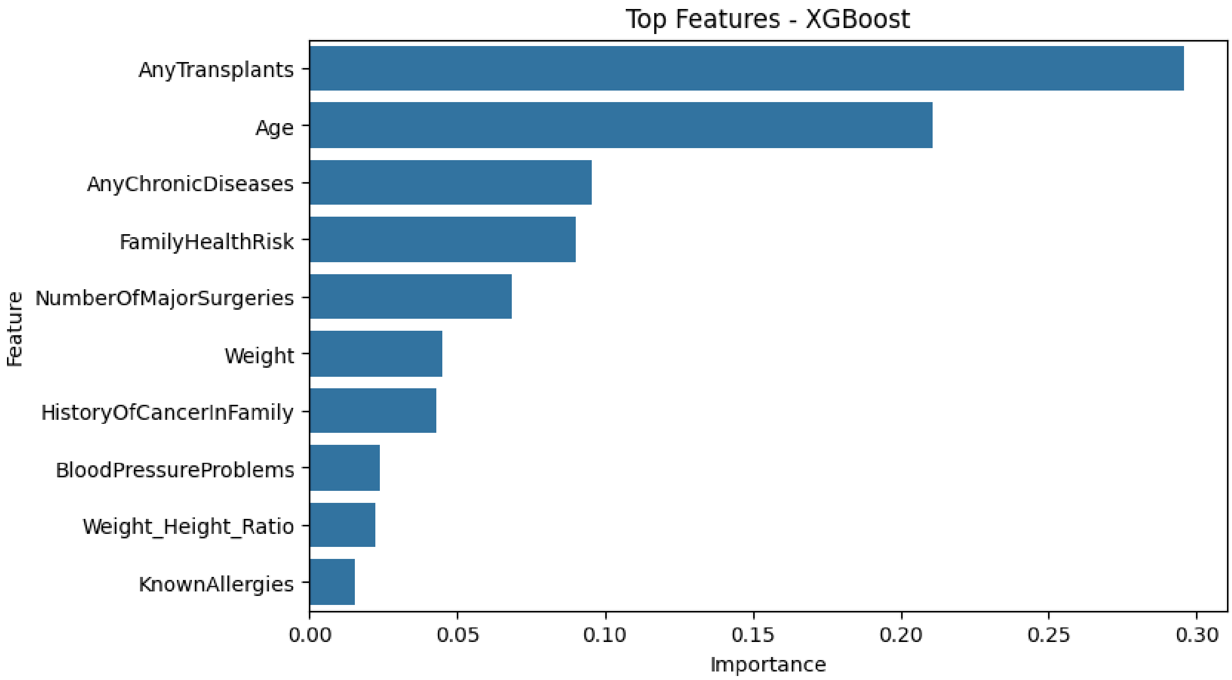
In [57]:
```
# Feature Importance

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


Top Features - Random Forest
Feature
Age
AnyTransplants
Weight
Weight_Height_Ratio
BMI
NumberOfMajorSurgeries
AnyChronicDiseases
FamilyHealthRisk
Age_ChronicInteraction
Surgery_ChronicInteraction
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 R^2 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 R^2 (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
```

In [73]:
```
X_sample
```

Out[73]:

	Age	Diabetes	BloodPressureProblems	AnyTransplants	AnyChronicDi:
613	0.591458	0	0	0	

1 rows × 24 columns