Importing libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import OneHotEncoder, PolynomialFeatures, PowerTransformer, F
from sklearn.compose import ColumnTransformer
```

Loading Dataset

In [2]:
```
df = pd.read_csv("/content/medical_insurance.csv")
```

EDA

In [3]:
```
df.sample(5)
```

Out[3]:

	age	sex	bmi	children	smoker	region	charges
2529	39	male	32.340	2	no	southeast	6338.07560
2725	56	female	39.820	0	no	southeast	11090.71780
2112	41	male	28.405	1	no	northwest	6664.68595
2751	46	male	25.800	5	no	southwest	10096.97000
312	43	male	35.970	3	yes	southeast	42124.51530

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2772 entries, 0 to 2771
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       2772 non-null   int64  
 1   sex       2772 non-null   object 
 2   bmi       2772 non-null   float64
 3   children  2772 non-null   int64  
 4   smoker    2772 non-null   object 
 5   region    2772 non-null   object 
 6   charges   2772 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 151.7+ KB
```

In [5]:
```
df.describe()
```

Out[5]:

	age	bmi	children	charges
count	2772.000000	2772.000000	2772.000000	2772.000000
mean	39.109668	30.701349	1.101732	13261.369959
std	14.081459	6.129449	1.214806	12151.768945
min	18.000000	15.960000	0.000000	1121.873900
25%	26.000000	26.220000	0.000000	4687.797000
50%	39.000000	30.447500	1.000000	9333.014350
75%	51.000000	34.770000	2.000000	16577.779500
max	64.000000	53.130000	5.000000	63770.428010

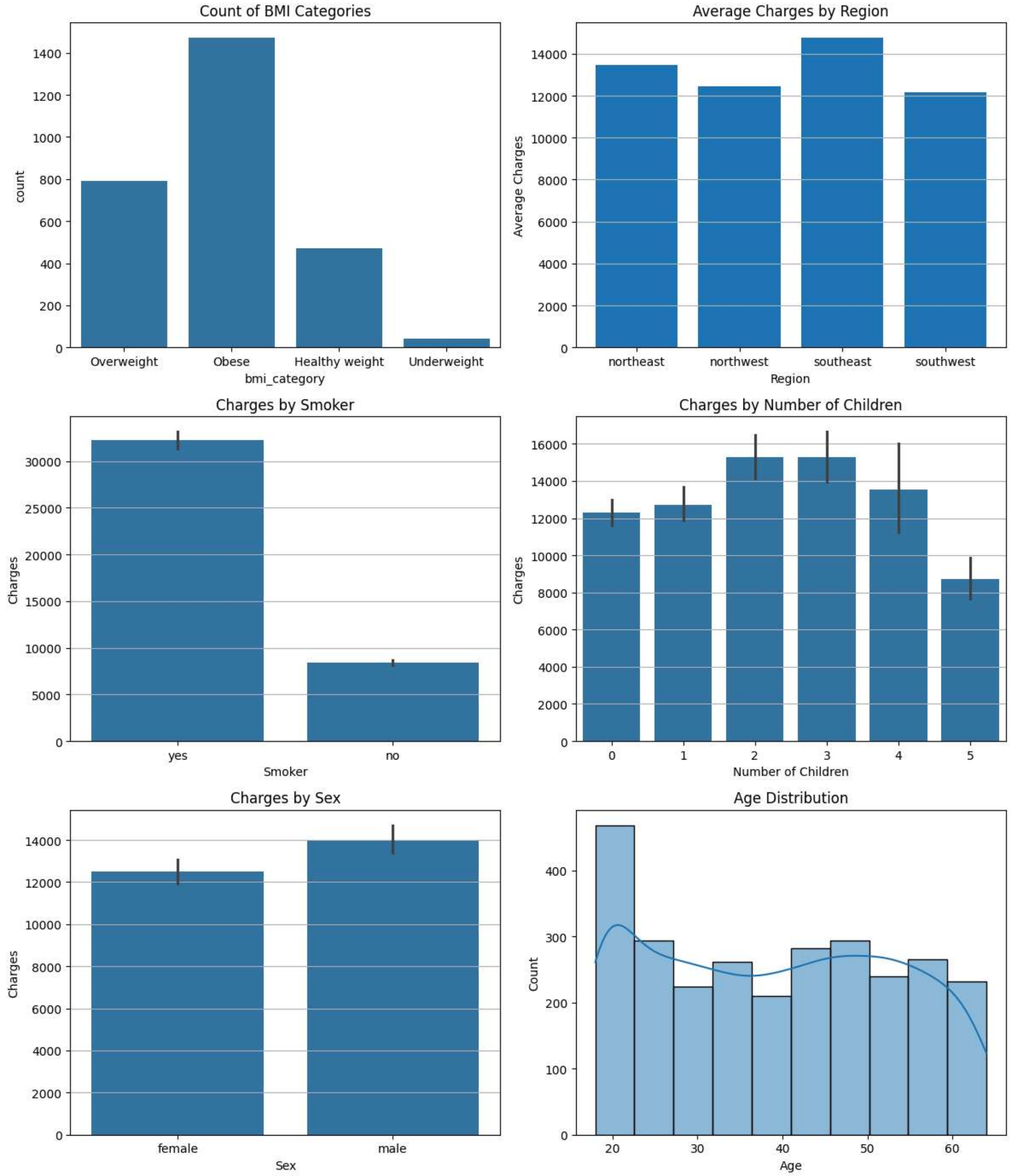
In [6]:
```
df.shape
```
Out[6]:
```
(2772, 7)
```

In [7]:
```
df.isnull().sum()
```
Out[7]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

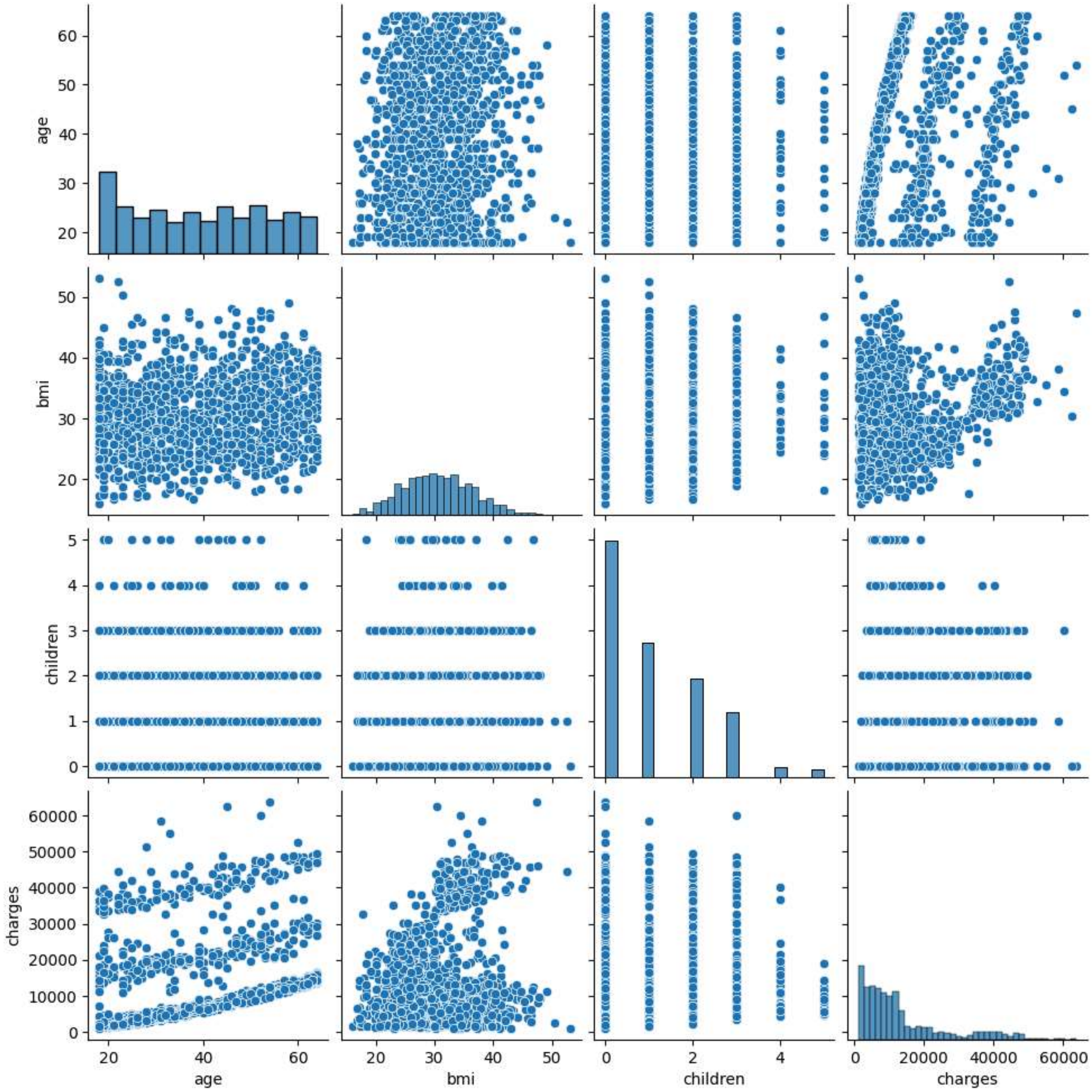
In [8]:
```
# Creating new column bmi_category
def categorize_bmi(bmi):
    if bmi < 18.5:
        return 'Underweight'
    elif 18.5 <= bmi < 25:
        return 'Healthy weight'
    elif 25 <= bmi < 30:
        return 'Overweight'
    else:
        return 'Obese'

df['bmi_category'] = df['bmi'].apply(categorize_bmi)
```

In [9]:
```
fig, axs = plt.subplots(3, 2, figsize=(12,14))

sns.countplot(x='bmi_category', data=df, ax=axs[0, 0])
axs[0, 0].set_title('Count of BMI Categories')

average_charges_by_region = df.groupby('region')['charges'].mean().reset_index()
axs[0, 1].bar(average_charges_by_region['region'], average_charges_by_region['charges'])
axs[0, 1].set_title('Average Charges by Region')
axs[0, 1].set_xlabel('Region')
axs[0, 1].set_ylabel('Average Charges')
axs[0, 1].grid(axis='y')

sns.barplot(x='smoker', y='charges', data=df, ax=axs[1, 0])
axs[1, 0].set_title('Charges by Smoker')
```

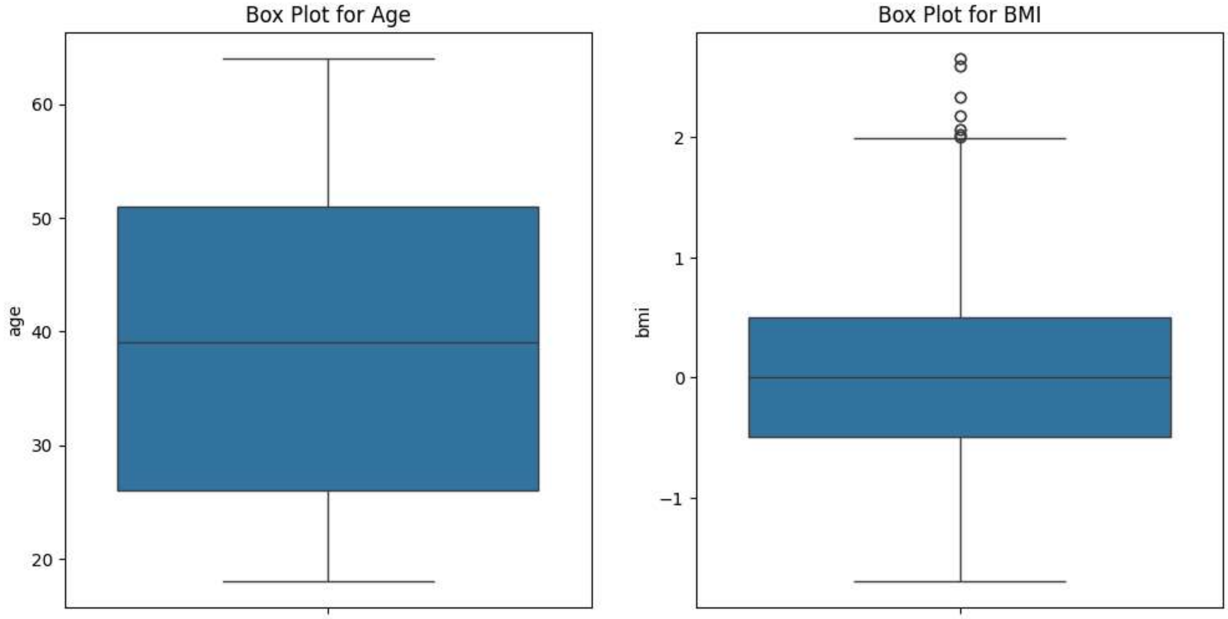
```
axs[1, 0].set_xlabel('Smoker')
axs[1, 0].set_ylabel('Charges')
axs[1, 0].grid(axis='y')

sns.barplot(x='children', y='charges', data=df, ax=axs[1, 1])
axs[1, 1].set_title('Charges by Number of Children')
axs[1, 1].set_xlabel('Number of Children')
axs[1, 1].set_ylabel('Charges')
axs[1, 1].grid(axis='y')

sns.barplot(x='sex', y='charges', data=df, ax=axs[2, 0])
axs[2, 0].set_title('Charges by Sex')
axs[2, 0].set_xlabel('Sex')
axs[2, 0].set_ylabel('Charges')
axs[2, 0].grid(axis='y')

sns.histplot(df['age'], bins=10, kde=True, ax=axs[2, 1])
axs[2, 1].set_title('Age Distribution')
axs[2, 1].set_xlabel('Age')
axs[2, 1].set_ylabel('Count')

# Adjust layout
plt.tight_layout()

# Show plots
plt.show()
```



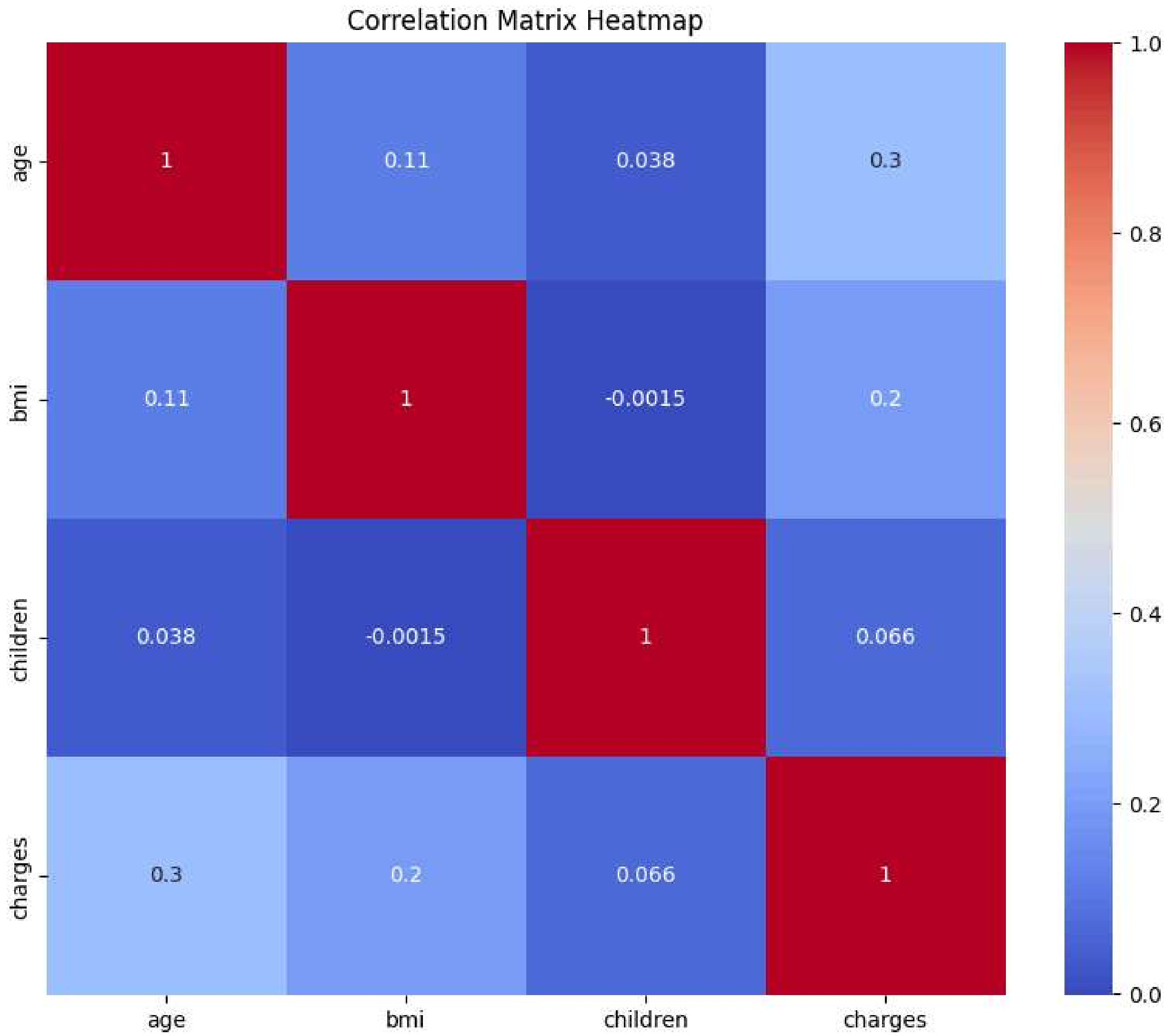
In [10]:
```
sns.pairplot(data=df)
plt.show()
```



In [20]:
```
fig, axs = plt.subplots(1, 2, figsize=(12, 6))

sns.boxplot(y='age', data=df, ax=axs[0])
axs[0].set_title('Box Plot for Age')

sns.boxplot(y='bmi', data=df, ax=axs[1])
axs[1].set_title('Box Plot for BMI')

plt.show()
```



In [12]:
```
numerical_columns = df.select_dtypes(include=['float64', 'int64'])

# correlation matrix
corr_matrix = numerical_columns.corr()

plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix Heatmap')
plt.show()
```



Scaling BMI values

In [13]:
```
scaler = RobustScaler()

df[['bmi']] = scaler.fit_transform(df[['bmi']])

print(df.head())
```

```
   age     sex       bmi  children smoker     region      charges  \
0   19  female -0.297953         0    yes  southwest  16884.92400
1   18    male  0.388596         1     no  southeast   1725.55230
2   28    male  0.298538         3     no  southeast   4449.46200
3   33    male -0.905556         0     no  northwest  21984.47061
4   32    male -0.183333         0     no  northwest   3866.85520

     bmi_category
0      Overweight
1           Obese
2           Obese
3  Healthy weight
4      Overweight
```

Spliting data into training and testing set

In [14]:
```
x=df.drop(columns=['charges','bmi_category'])
y=df['charges']
```

In [15]:
```
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.25,random_state=100)
```

Data Transformation: Encoding Categorical Variables and Normalizing Age

In [16]:
```
transformer = ColumnTransformer(transformers=[
    ('tnf1',OneHotEncoder(sparse=True),['sex','smoker','region']),
    ('yeo-johnson', PowerTransformer(), ['age'])
],remainder='passthrough')

x_train_transformed=transformer.fit_transform(x_train)
x_test_transformed=transformer.transform(x_test)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_encoders.py:868: FutureW
arning: `sparse` was renamed to `sparse_output` in version 1.2 and will be removed in
1.4. `sparse_output` is ignored unless you leave `sparse` to its default value.
  warnings.warn(
```

Linear Regression Model

In [17]:
```
linear_reg_model = LinearRegression()
linear_reg_model.fit(x_train_transformed, y_train)

y_test_pred_lr = linear_reg_model.predict(x_test_transformed)

mse = mean_squared_error(y_test, y_test_pred_lr)
r2 = r2_score(y_test, y_test_pred_lr)

print("Mean Squared Error (MSE):", mse)
print("R-squared (R2) score:", r2)
```

```
Mean Squared Error (MSE): 33871092.73593269
R-squared (R2) score: 0.7416513635070527
```

Polynomial Regression Model

In [31]:
```
poly_features = PolynomialFeatures(degree=2)

x_train_poly = poly_features.fit_transform(x_train_transformed)
x_test_poly = poly_features.transform(x_test_transformed)

poly_reg_model = LinearRegression()
poly_reg_model.fit(x_train_poly, y_train)

y_test_pred_poly=poly_reg_model.predict(x_test_poly)

mse = mean_squared_error(y_test, y_test_pred_poly)
r2 = r2_score(y_test, y_test_pred_poly)

print("Mean Squared Error (MSE):", mse)
print("R-squared (R2) score:", r2)
```

```
Mean Squared Error (MSE): 22251448.559211314
R-squared (R2) score: 0.8302791279843572
```

In [34]:
```
# cross-validation
cv_scores = cross_val_score(poly_reg_model, x_test_poly, y_test, cv=10, scoring='r2')

# mean R2 score
mean_cv_score = np.mean(cv_scores)
print("Mean Cross-Validation R2 score:", mean_cv_score)
```

```
Mean Cross-Validation R2 score: 0.8199606611225512
```

Conclusion

During analysis of the medical insurance dataset, several key insights were uncovered:

- 🚬 **Smokers tend to incur higher insurance charges**, highlighting the impact of lifestyle choices on healthcare costs.
- 🍔 **Obesity is associated with increased medical expenses**, underscoring the importance of preventive healthcare measures.
- 🌎 **Individuals from the southeast region consistently pay higher charges**, suggesting regional variations in healthcare costs.
- 👨‍👩‍👧‍👦 **Families with 2 or 3 dependent children face higher insurance charges**, indicating the influence of family size on healthcare expenditures.
- 🎓 **Interestingly, young adults in the age range of 20-25 tend to pay higher charges compared to other age groups**, possibly due to lifestyle factors or limited access to preventive care.

These findings provide valuable insights into the factors influencing healthcare costs in our dataset.

Modeling Approach

For predictive modeling, I used polynomial regression with a degree of 2 instead of linear regression. The decision to use polynomial regression was to capture potentially complex relationships between the features and the target variable that may not be adequately captured by a linear model.

Polynomial regression allows us to model nonlinear relationships by introducing polynomial terms, enabling the model to better fit the data and potentially improve predictive performance. By using a polynomial regression model with a degree of 2, I aimed to capture quadratic relationships between the features and the target variable.