Healthcare Claim Analysis Project

1. Introduction

This project focuses on leveraging data analytics to extract meaningful insights from a healthcare dataset. By analyzing the data, building a predictive model, and creating visualizations, the project demonstrates how data can support decision-making in healthcare.

The dataset used in this project contains key healthcare-related variables, which were cleaned and analyzed to uncover patterns and trends. A user-interactive model was built to take inputs and provide predictions, helping to simulate real-world scenarios in healthcare. The findings and results are visualized using Power BI dashboards, making the insights more accessible and impactful for stakeholders.

2. Data Loading and Initial Inspection

In [1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:
```
df = pd.read_csv("C:/Users/ratne/Downloads/healthinsurance_insurance.csv")
```

In [3]:
```
df.head(10)
```

Out[3]:

	age	sex	weight	bmi	hereditary_diseases	no_of_dependents	smoker	city	bl
0	60.0	male	64	24.3	NoDisease	1	0	NewYork	
1	49.0	female	75	22.6	NoDisease	1	0	Boston	
2	32.0	female	64	17.8	Epilepsy	2	1	Phildelphia	
3	61.0	female	53	36.4	NoDisease	1	1	Pittsburg	
4	19.0	female	50	20.6	NoDisease	0	0	Buffalo	
5	42.0	female	89	37.9	NoDisease	0	0	AtlanticCity	
6	18.0	male	59	23.8	NoDisease	0	0	Portland	
7	21.0	male	52	26.8	NoDisease	0	0	Cambridge	
8	63.0	male	55	NaN	NoDisease	0	0	Hartford	
9	40.0	female	69	29.6	NoDisease	0	0	Springfield	

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15000 entries, 0 to 14999
Data columns (total 13 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   age                 14604 non-null  float64
 1   sex                 15000 non-null  object 
 2   weight              15000 non-null  int64  
 3   bmi                 14044 non-null  float64
 4   hereditary_diseases 15000 non-null  object 
 5   no_of_dependents    15000 non-null  int64  
 6   smoker              15000 non-null  int64  
 7   city                15000 non-null  object 
 8   bloodpressure       15000 non-null  int64  
 9   diabetes            15000 non-null  int64  
 10  regular_ex          15000 non-null  int64  
 11  job_title           15000 non-null  object 
 12  claim               15000 non-null  float64
dtypes: float64(3), int64(6), object(4)
memory usage: 1.5+ MB
```

In [5]:
```python
df.select_dtypes(include = 'number').head(10)
```

Out[5]:

	age	weight	bmi	no_of_dependents	smoker	bloodpressure	diabetes	regular_ex	cla
0	60.0	64	24.3	1	0	72	0	0	13112
1	49.0	75	22.6	1	0	78	1	1	9567
2	32.0	64	17.8	2	1	88	1	1	32734
3	61.0	53	36.4	1	1	72	1	0	48517
4	19.0	50	20.6	0	0	82	1	0	1731
5	42.0	89	37.9	0	0	78	0	0	6474
6	18.0	59	23.8	0	0	64	0	0	1705
7	21.0	52	26.8	0	0	74	1	0	1534
8	63.0	55	NaN	0	0	70	1	0	13390
9	40.0	69	29.6	0	0	64	1	1	5910

In [6]:
```
df.describe()
```

Out[6]:

	age	weight	bmi	no_of_dependents	smoker	bloodpres
count	14604.000000	15000.000000	14044.000000	15000.000000	15000.000000	15000.00
mean	39.547521	64.909600	30.266413	1.129733	0.198133	68.65
std	14.015966	13.701935	6.122950	1.228469	0.398606	19.41
min	18.000000	34.000000	16.000000	0.000000	0.000000	0.00
25%	27.000000	54.000000	25.700000	0.000000	0.000000	64.00
50%	40.000000	63.000000	29.400000	1.000000	0.000000	71.00
75%	52.000000	76.000000	34.400000	2.000000	0.000000	80.00
max	64.000000	95.000000	53.100000	5.000000	1.000000	122.00

In [7]:
```
df.describe().T
```

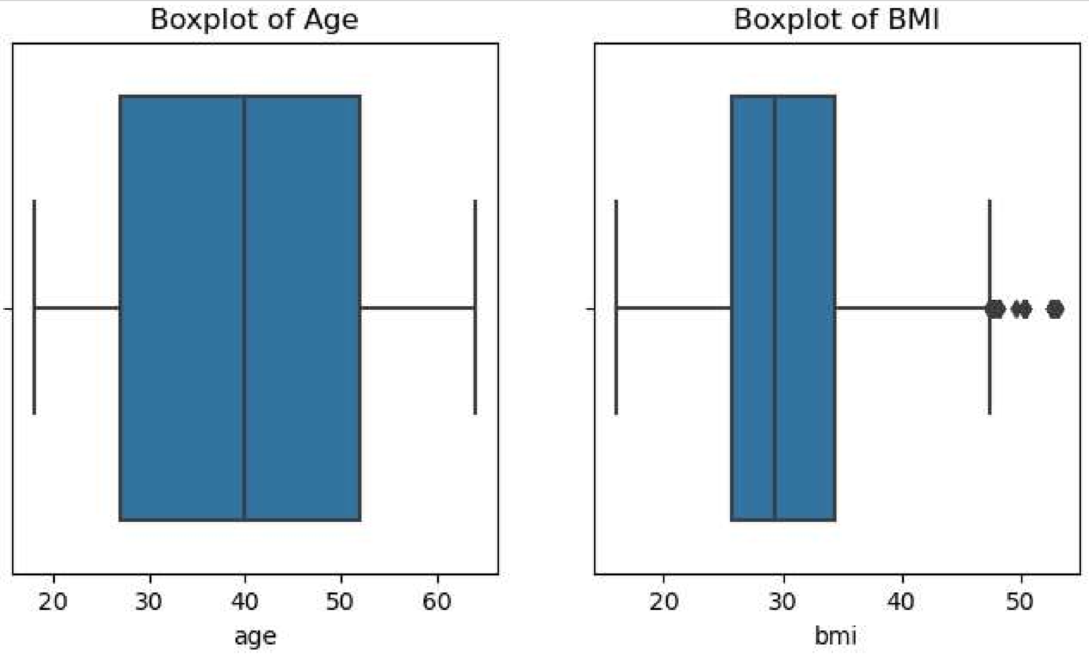
Out[7]:

	count	mean	std	min	25%	50%	75%
age	14604.0	39.547521	14.015966	18.0	27.0	40.00	52.000
weight	15000.0	64.909600	13.701935	34.0	54.0	63.00	76.000
bmi	14044.0	30.266413	6.122950	16.0	25.7	29.40	34.400
no_of_dependents	15000.0	1.129733	1.228469	0.0	0.0	1.00	2.000
smoker	15000.0	0.198133	0.398606	0.0	0.0	0.00	0.000
bloodpressure	15000.0	68.650133	19.418515	0.0	64.0	71.00	80.000
diabetes	15000.0	0.777000	0.416272	0.0	1.0	1.00	1.000
regular_ex	15000.0	0.224133	0.417024	0.0	0.0	0.00	0.000
claim	15000.0	13401.437620	12148.239619	1121.9	4846.9	9545.65	16519.125

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
age                  396
sex                    0
weight                 0
bmi                  956
hereditary_diseases    0
no_of_dependents       0
smoker                 0
city                   0
bloodpressure          0
diabetes               0
regular_ex             0
job_title              0
claim                  0
dtype: int64
```

In [9]:
```
plt.figure(figsize = (8,4))


plt.subplot(1,2,1)
sns.boxplot(x = df["age"])
plt.title("Boxplot of Age")


plt.subplot(1,2,2)
sns.boxplot(x = df["bmi"])
plt.title("Boxplot of BMI")

plt.show()
```



Handling Missing Values

Missing values were identified in the age (396 missing) and bmi (956 missing) columns. These were filled with the median rather than the mean due to the presence of outliers in both columns. The boxplots for age and bmi showed extreme values that could distort the mean. Since the median is less sensitive to outliers, it offers a more robust method for imputation, better reflecting the overall distribution of the data.

In [10]:
```
df.fillna(df['age'].median(), inplace = True)
df.fillna(df['bmi'].median(), inplace = True)
```

In [11]:

```
df.isnull().sum()
```

Out[11]:

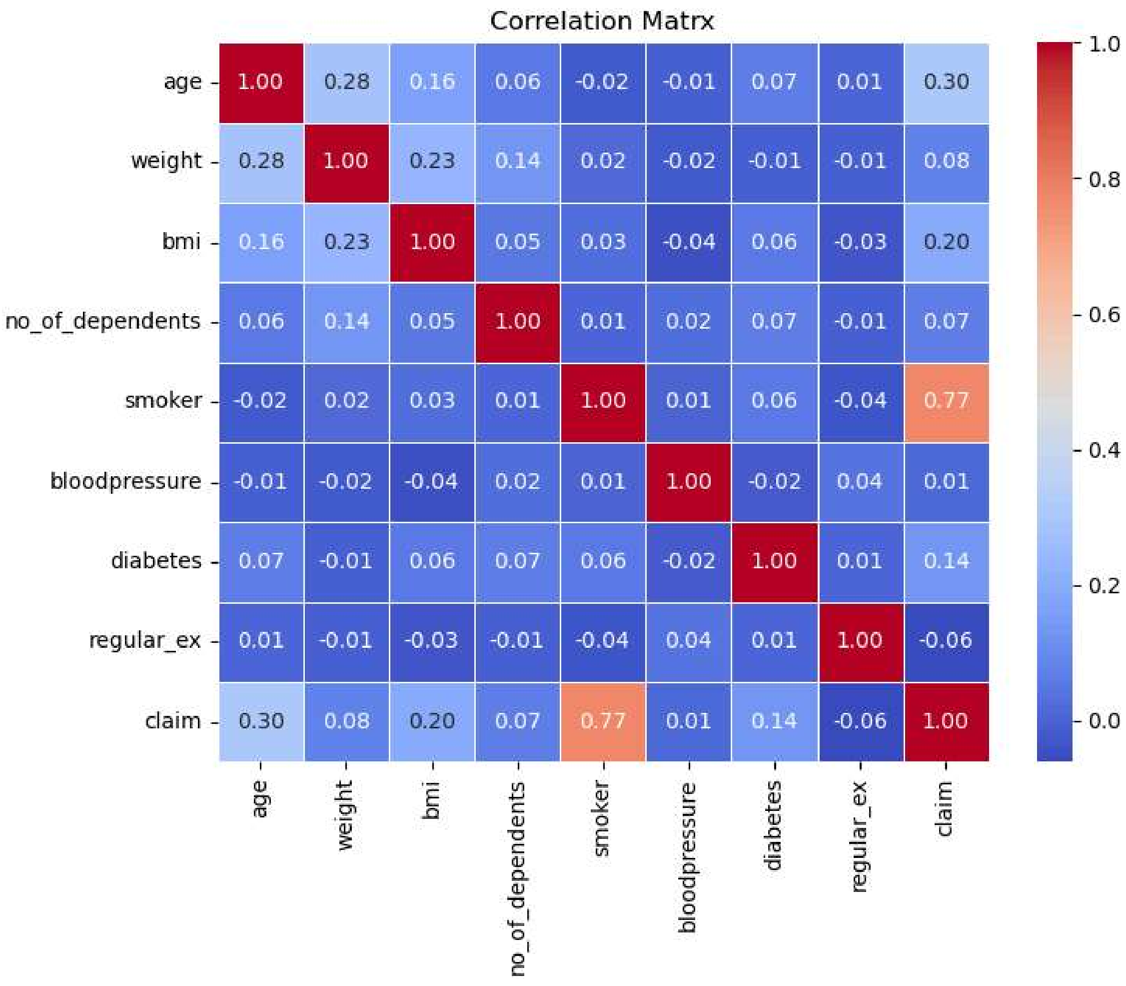
```
age                  0
sex                  0
weight               0
bmi                  0
hereditary_diseases  0
no_of_dependents     0
smoker               0
city                 0
bloodpressure        0
diabetes             0
regular_ex           0
job_title            0
claim                0
dtype: int64
```

Correlation Analysis

In [12]:

```
plt.figure(figsize = (8,6))
corr = df.corr()
sns.heatmap(corr, annot= True, cmap = 'coolwarm', fmt = '.2f', linewidths =
plt.title('Correlation Matrx')
plt.show()
```

```
C:\Users\ratne\AppData\Local\Temp\ipykernel_16756\205097137.py:2: FutureWa
rning: The default value of numeric_only in DataFrame.corr is deprecated.
In a future version, it will default to False. Select only valid columns o
r specify the value of numeric_only to silence this warning.
  corr = df.corr()
```



	age	weight	bmi	no_of_dependents	smoker	bloodpressure	diabetes	regular_ex	claim
age	1.00	0.28	0.16	0.06	-0.02	-0.01	0.07	0.01	0.30
weight	0.28	1.00	0.23	0.14	0.02	-0.02	-0.01	-0.01	0.08
bmi	0.16	0.23	1.00	0.05	0.03	-0.04	0.06	-0.03	0.20
no_of_dependents	0.06	0.14	0.05	1.00	0.01	0.02	0.07	-0.01	0.07
smoker	-0.02	0.02	0.03	0.01	1.00	0.01	0.06	-0.04	0.77
bloodpressure	-0.01	-0.02	-0.04	0.02	0.01	1.00	-0.02	0.04	0.01
diabetes	0.07	-0.01	0.06	0.07	0.06	-0.02	1.00	0.01	0.14
regular_ex	0.01	-0.01	-0.03	-0.01	-0.04	0.04	0.01	1.00	-0.06
claim	0.30	0.08	0.20	0.07	0.77	0.01	0.14	-0.06	1.00

Insights

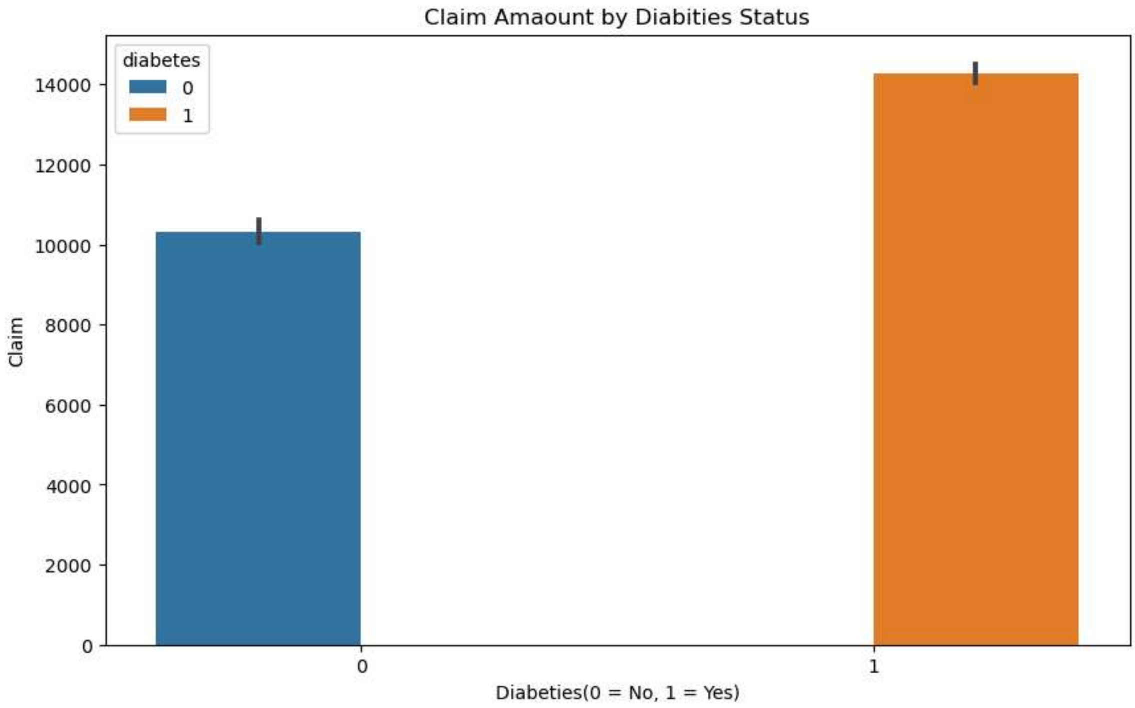
- The heatmap reveals a strong positive correlation between bmi, smoker, and claim. This suggests that higher BMI and smoking status are associated with higher healthcare claims, indicating that these are crucial factors in predicting insurance costs.
- age and claim also show a positive correlation, albeit weaker than BMI and smoking. This suggests that as individuals age, their healthcare needs increase, resulting in higher claims.

3. Claim Analysis Based on Key Factors

Diabetes and Claims

In [13]:

```
plt.figure(figsize = (10,6))
sns.barplot(x = 'diabetes', y = 'claim', hue = 'diabetes', data = df)
plt.title('Claim Amaount by Diabities Status')
plt.xlabel('Diabeties(0 = No, 1 = Yes)')
plt.ylabel('Claim')
plt.show()
```

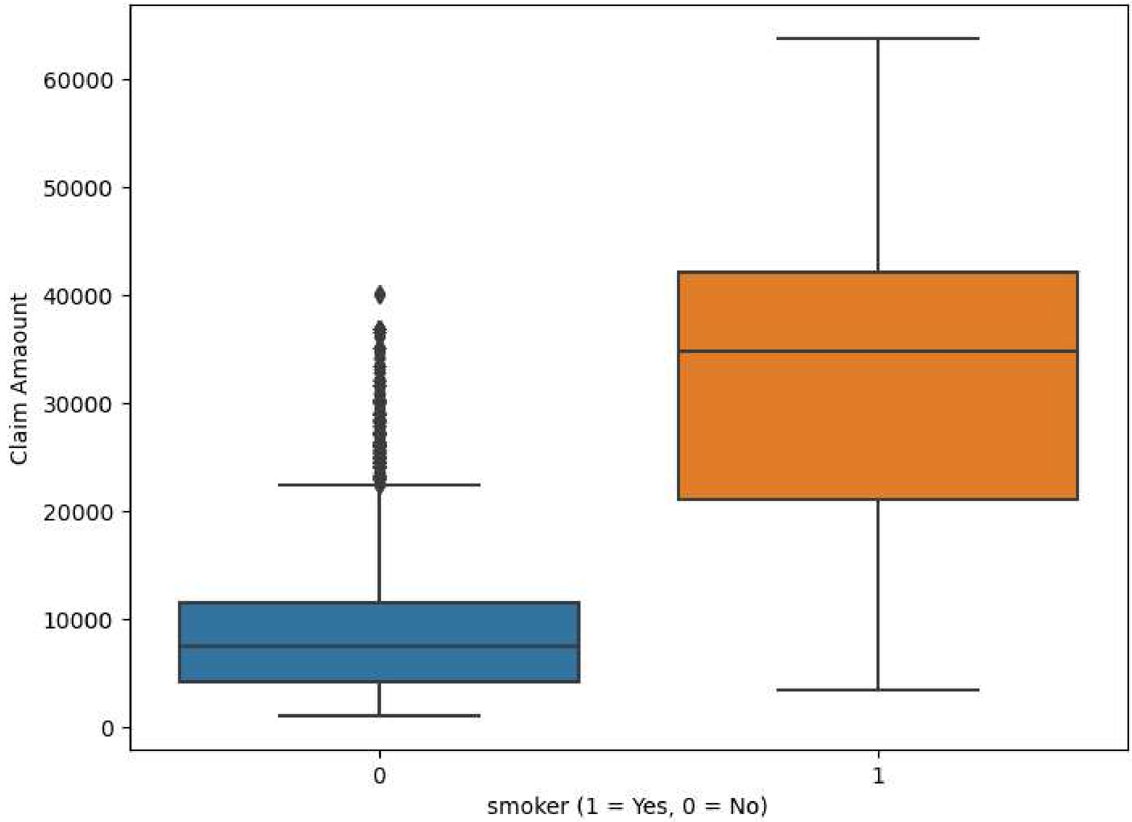


Insights

- From the graph, diabetic patients consistently exhibit higher claim amounts than non-diabetic individuals, highlighting the financial burden of managing diabetes.
- Claims for diabetic patients generally range between 2500 and 5000, with severe cases surpassing 10000, driven by complications and advanced treatments.
- Introducing risk-adjusted premiums and optional riders for complications can help insurers manage costs while encouraging preventive care to reduce high-risk claims.

Smoker and Claim

In [14]:
```
plt.figure(figsize = (8,6))
sns.boxplot(x = 'smoker', y = 'claim', data = df)
plt.xlabel('Claim Amount by Smoker')
plt.ylabel('Claim Amaount')
plt.xlabel('smoker (1 = Yes, 0 = No)')
plt.show()
```

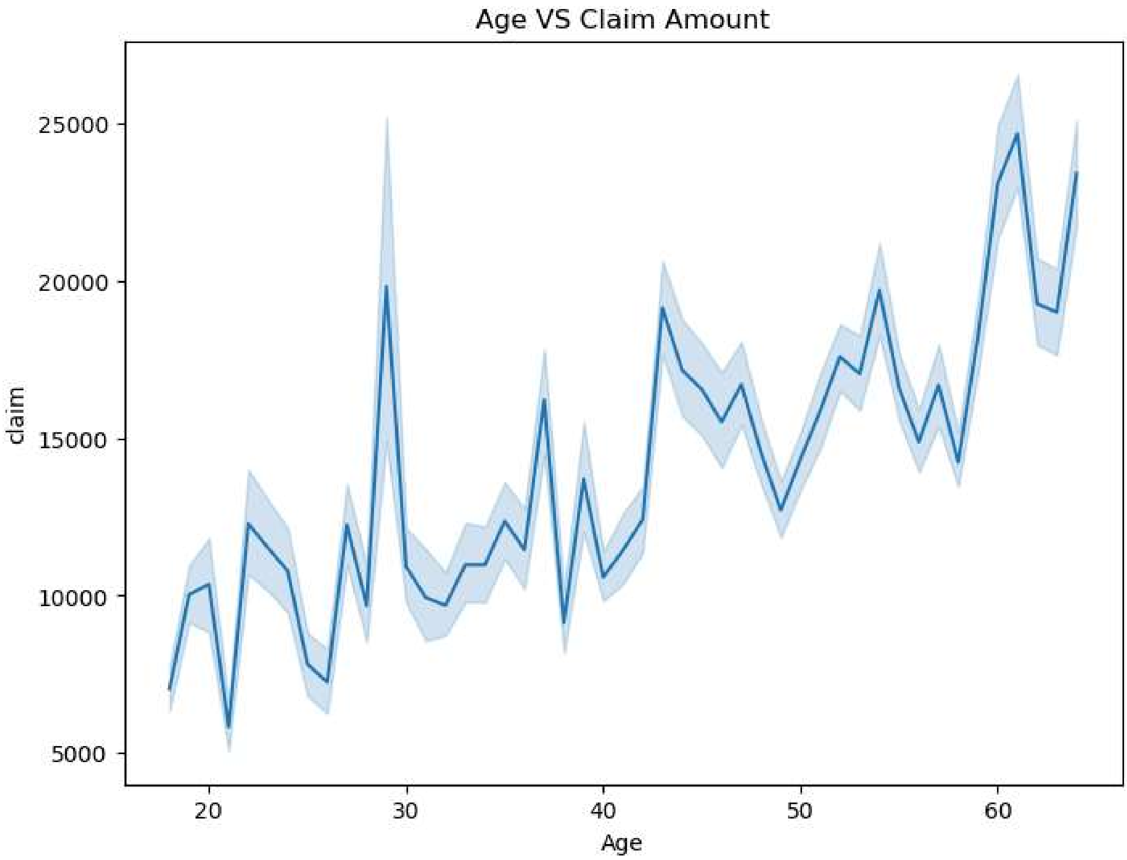


Insights

- The graph shows smokers generally have higher claim amounts with a wider range of values compared to non-smokers.
- Outliers in the non-smoker group indicate a few individuals with exceptionally high claim amounts. This could be due to data anomalies, rare conditions, or isolated high-cost treatments, which deviate from the general trend seen for non-smokers.
- Non-smokers typically exhibit a more concentrated claim distribution at lower levels, whereas smokers show a broader distribution with consistently higher values.

Age and Claims

In [15]:
```
plt.figure(figsize = (8,6))
sns.lineplot(x = 'age', y = 'claim', data = df)
plt.title('Age VS Claim Amount')
plt.xlabel('Age')
plt.ylabel('claim')
plt.show()

correlation_age = df['age'].corr(df['claim'])
print(f"Correlation between Age and Claim Amount: {correlation_age:.2f}")
```



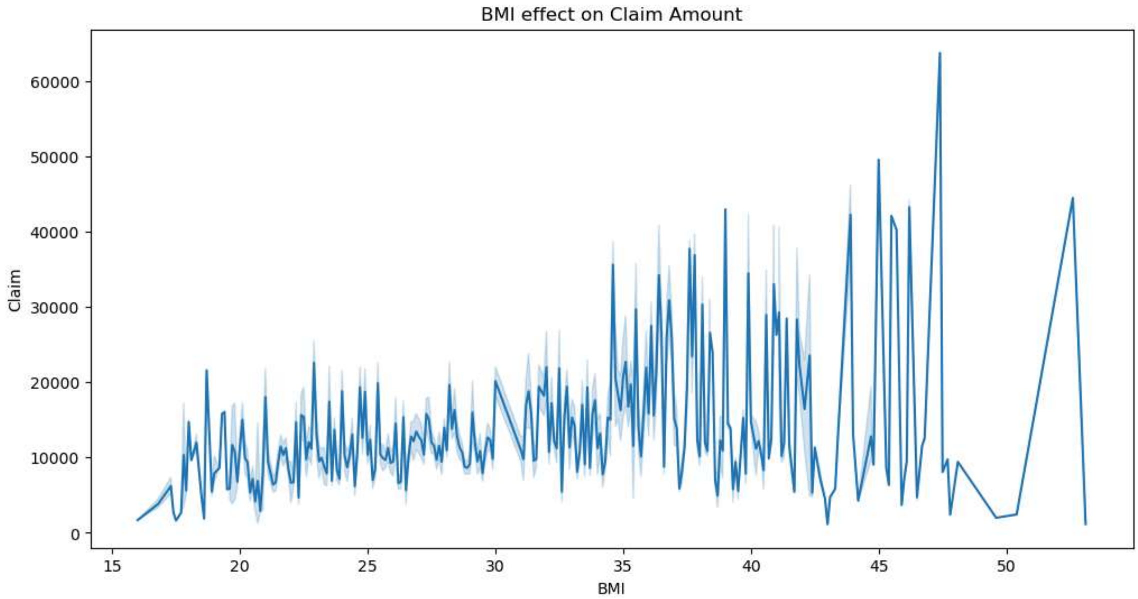

```
Correlation between Age and Claim Amount: 0.30
```

Insights

- The line graph shows a clear upward trend in claim amounts with increasing age, indicating that older individuals tend to incur higher healthcare costs compared to younger age groups.
- There is a noticeable steep rise in claim amounts after a certain age threshold (e.g., 50+), which suggests that healthcare needs significantly escalate as individuals age.
- Younger age groups exhibit relatively stable and lower claim amounts, reflecting fewer healthcare expenses compared to older populations, where variability and cost intensity increase.

BMI and Claims

In [18]:
```
plt.figure(figsize = (12,6))
sns.lineplot(x = 'bmi', y = 'claim', data = df)
plt.xlabel('BMI')
plt.ylabel('Claim')
plt.title('BMI effect on Claim Amount')
plt.show()
```



In [19]:
```
bins = [15, 20, 25, 30, 35, 40, 45, 50]

df['bmi_range'] = pd.cut(df['bmi'], bins = bins)

bmi_range_counts = df['bmi_range'].value_counts().sort_index()

print('Number of People in each BMI range :')
print(bmi_range_counts)
```

```
Number of People in each BMI range :
(15, 20]     418
(20, 25]    2422
(25, 30]    4815
(30, 35]    3264
(35, 40]    3213
(40, 45]     642
(45, 50]     192
Name: bmi_range, dtype: int64
```

Insights

- The graph shows a positive trend between BMI and claim amounts, indicating that individuals with higher BMI tend to incur higher claims. This suggests a correlation between increased BMI and higher healthcare costs.
- The claim amounts begin to rise sharply for individuals with BMI above a certain threshold (e.g., 30+), reflecting potentially higher medical needs associated with elevated BMI levels.

- Individuals with lower BMI exhibit relatively stable and lower claim amounts, while higher BMI categories show greater variability, suggesting a wider range of medical expenses.

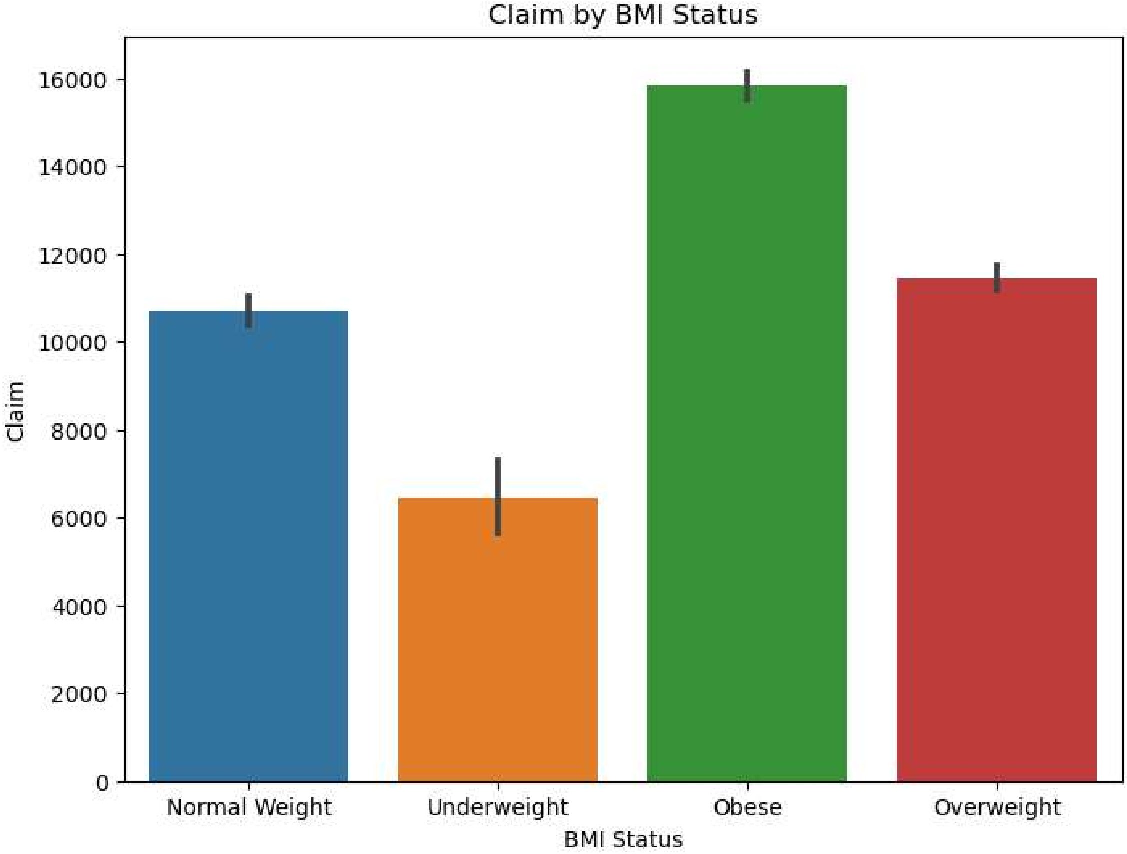
Reason for Lower Claims in Higher BMI Ranges:

The lower average claims in higher BMI categories (40-50) can be attributed to the smaller population sizes in these ranges: 642 in 40-45 and 192 in 45-50. Since the graph displays average claims, the smaller sample size makes the averages more sensitive to outliers (e.g., individuals with lower claims). Additionally, factors like reduced healthcare access or younger individuals without chronic conditions may also explain the trend

Claim Amount by BMI Status

In [20]:
```
def bmi_category_function(bmi):
    if bmi < 18.5:
        return 'Underweight'
    elif 18.5 <= bmi < 25:
        return 'Normal Weight'
    elif 25 <= bmi < 30:
        return 'Overweight'
    else:
        return 'Obese'
df['bmi_category'] = df['bmi'].apply(bmi_category_function)
```

In [21]:
```
plt.figure(figsize = (8,6))
sns.barplot(x = 'bmi_category', y = 'claim', data = df)
plt.title('Claim by BMI Status')
plt.xlabel('BMI Status')
plt.ylabel('Claim')
plt.show()
```

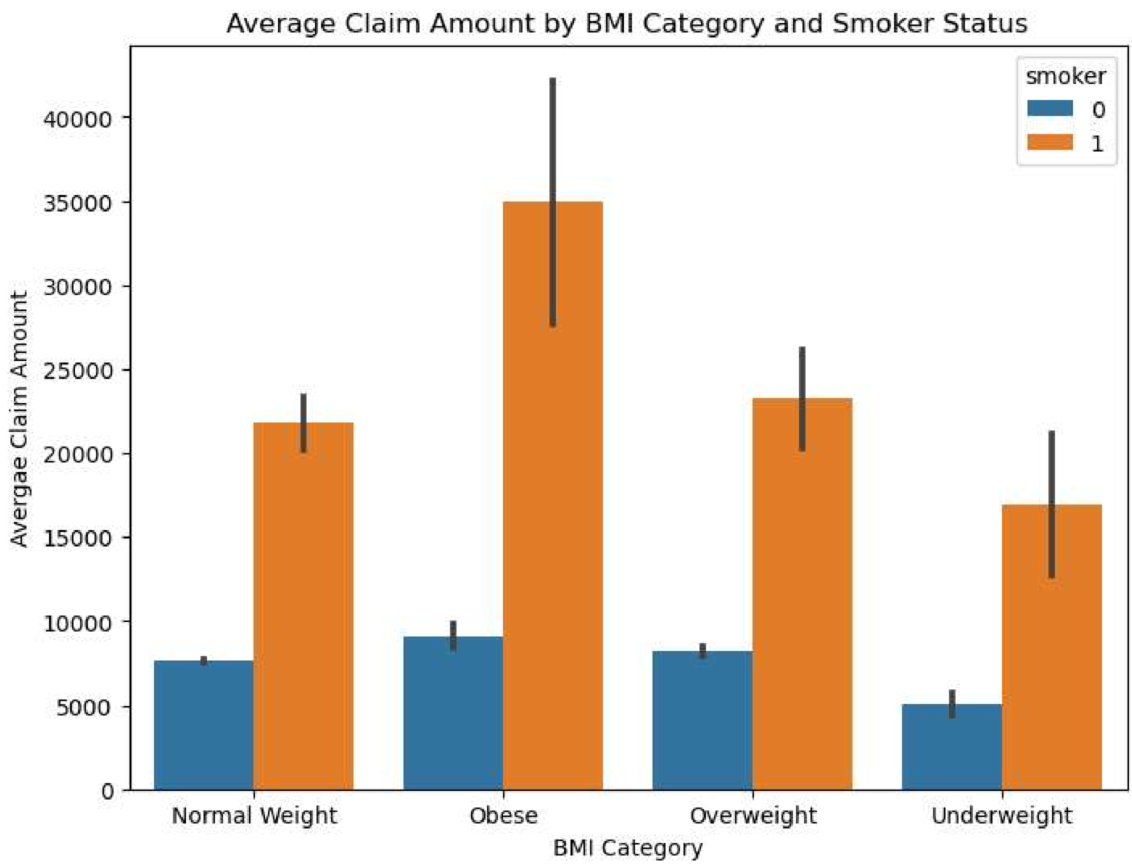


Insights

- Individuals with an "Obese" BMI status have significantly higher and more variable claim amounts, reflecting greater healthcare needs and cost variability.
- The "Overweight" group shows moderately higher claims than "Normal," suggesting that even slight increases in BMI contribute to higher costs.
- The "Normal" BMI status correlates with the lowest claim amounts, while outliers likely reflect unrelated high-cost treatments.

Comparison of Average Claim Amount by BMI Category and Smoker Status

In [22]:
```
combined_analysis = df.groupby(['smoker', 'diabetes', 'bmi_category'])['cla

plt.figure(figsize = (8,6))
sns.barplot(x = 'bmi_category', y = 'claim', hue = 'smoker', data = combine
plt.title('Average Claim Amount by BMI Category and Smoker Status')
plt.xlabel('BMI Category')
plt.ylabel('Avergae Claim Amount')
plt.show()
```



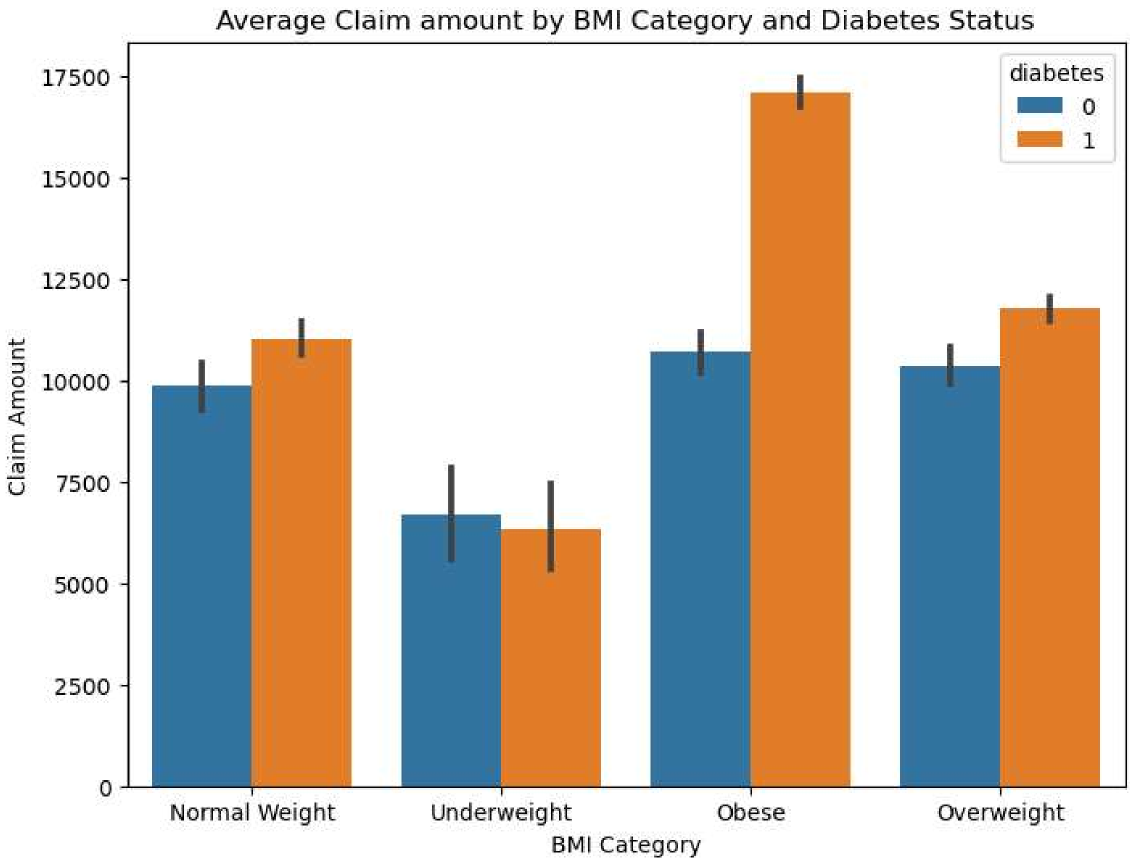
Insights

- The graph shows that smokers consistently incur higher claim amounts than non-smokers across all BMI categories. This suggests that smoking is a significant driver of healthcare costs, regardless of BMI, and amplifies the financial impact even within healthier BMI ranges.

- In the "Obese" BMI category, smokers have the highest average claim amounts among all groups. This indicates that the combination of high BMI and smoking leads to compounded health risks, resulting in significantly higher claims.
- Non-smokers in the "Normal Weight" category exhibit the lowest claim amounts, reflecting a correlation between healthier lifestyles and reduced healthcare costs. However, the "Underweight" category shows more variability in claim amounts for both smokers and non-smokers, which could indicate unique health conditions or outliers in this group.

Average Claim Amount by BMI Category and Diabetes Status

In [23]:
```
plt.figure(figsize = (8,6))
sns.barplot(x = 'bmi_category', y = 'claim', hue = 'diabetes', data = df)
plt.title('Average Claim amount by BMI Category and Diabetes Status')
plt.xlabel('BMI Category')
plt.ylabel('Claim Amount')
plt.show()
```



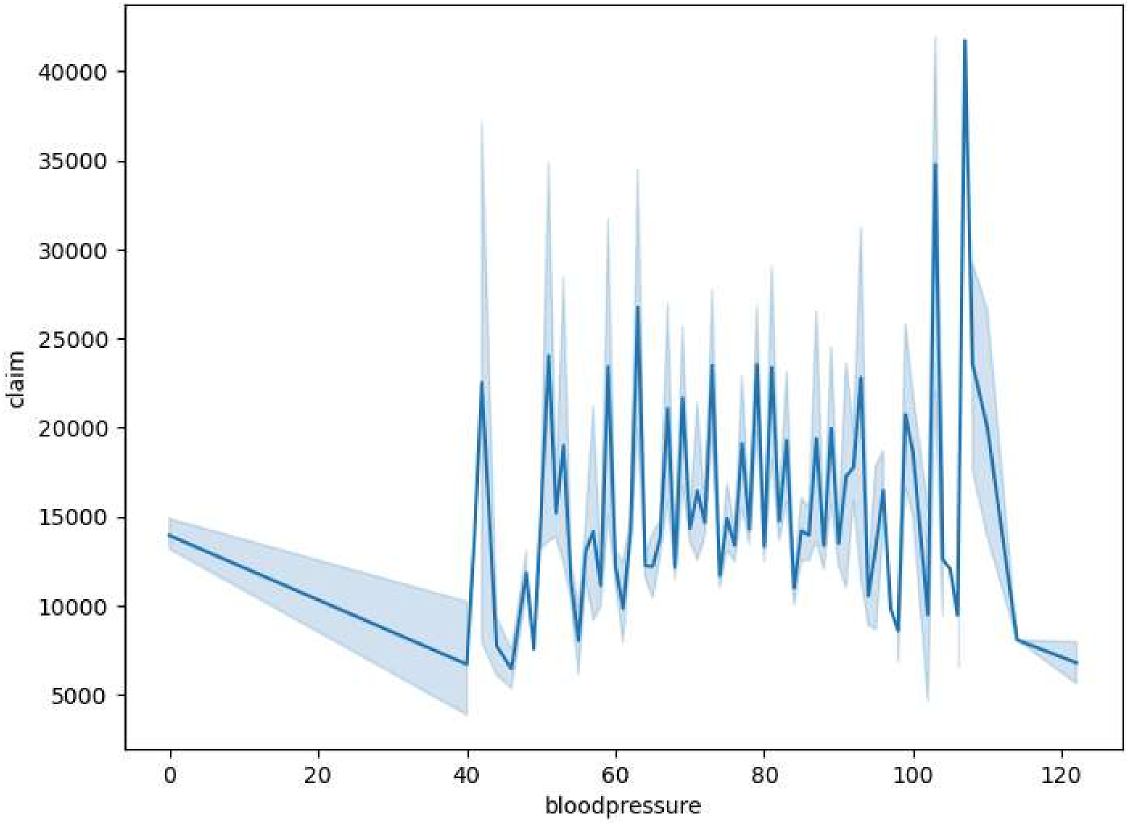
Insight

- Individuals with diabetes generally have higher average claim amounts compared to those without diabetes across all BMI categories. This trend is particularly pronounced in the "Obese" category, where claims are significantly elevated for diabetic individuals, highlighting the increased healthcare costs associated with managing diabetes in obese patients.
- Non-diabetic individuals maintain relatively consistent claim amounts across BMI categories, whereas diabetic individuals show a substantial rise, especially in the "Obese" category. This emphasizes the compounded financial burden of obesity and

diabetes on healthcare claims.

Bloodpressure and Claims

In [24]:
```
plt.figure(figsize = (8,6))
sns.lineplot(x = 'bloodpressure', y = 'claim', data = df)
plt.show()
```



In [35]:
```
bins = [10,50,60,70,80,90,100,120,130,140,180]
df['bp_range'] = pd.cut(df['bloodpressure'], bins = bins)

bp_range_count = df['bp_range'].value_counts().sort_index()
print(bp_range_count)
```

```
(10, 50]       454
(50, 60]      1795
(60, 70]      4484
(70, 80]      4539
(80, 90]      2310
(90, 100]      485
(100, 120]     149
(120, 130]      28
(130, 140]       0
(140, 180]       0
Name: bp_range, dtype: int64
```

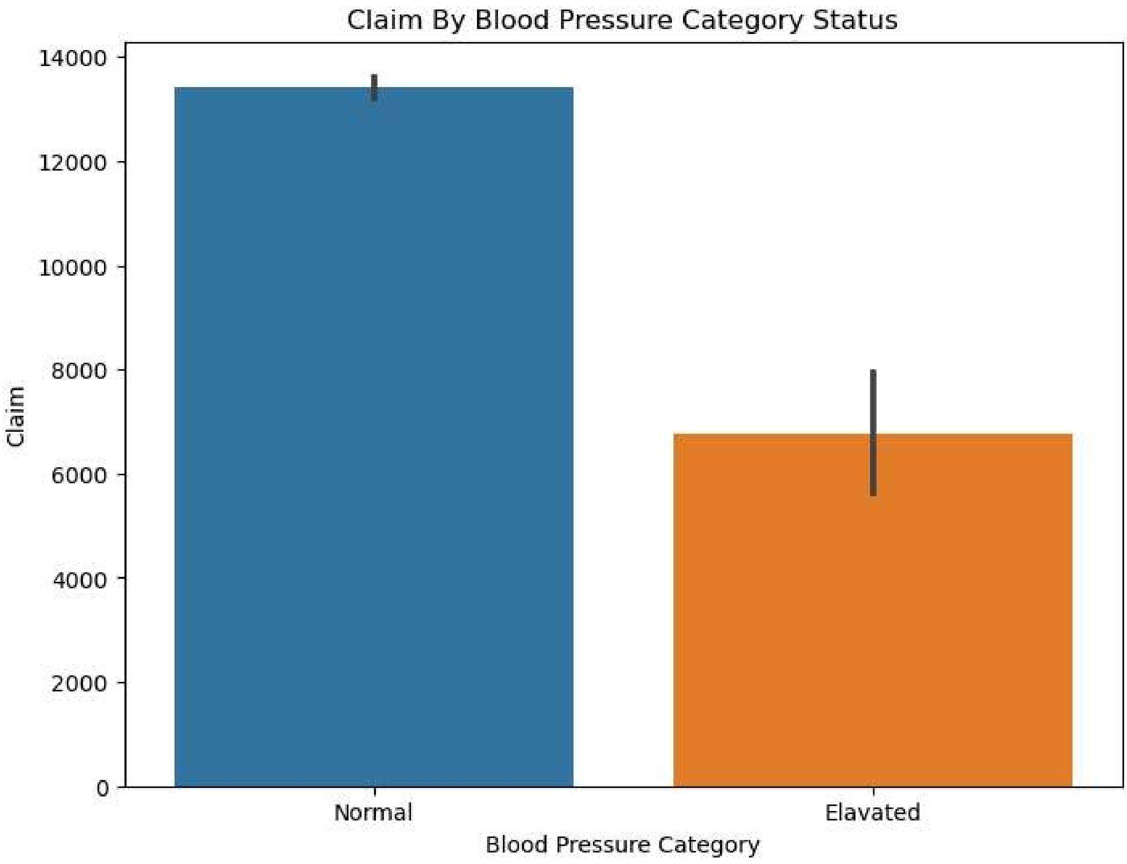
Insights

- The relationship between blood pressure levels and claim amounts is highly variable, with no consistent trend observed. This suggests that factors beyond blood pressure, such as other health or demographic variables, may significantly influence claim amounts.

- The majority of data points are concentrated in the 50–100 blood pressure range, with very few entries in higher ranges. This imbalance likely impacts the observed variability, as limited data in higher ranges may lead to less reliable insights.

In [26]:
```
def bp_category_function(bloodpressure):
    if pd.isna(bloodpressure):
        return 'Unknown'
    elif bloodpressure < 120:
        return 'Normal'
    elif 120 <= bloodpressure < 130:
        return 'Elavated'
    elif 130 <= bloodpressure < 140:
        return 'Hypertension Stage 1'
    elif 140 <= bloodpressure < 180:
        return 'Hypertension Stage 2'
    else:
        return 'Hypertensive Crisis'

df['bp_category'] = df['bloodpressure'].apply(bp_category_function)
```

In [27]:
```
plt.figure(figsize = (8,6))
sns.barplot(x = 'bp_category', y = 'claim', data = df)
plt.title('Claim By Blood Pressure Category Status')
plt.xlabel('Blood Pressure Category')
plt.ylabel('Claim')
plt.show()
```

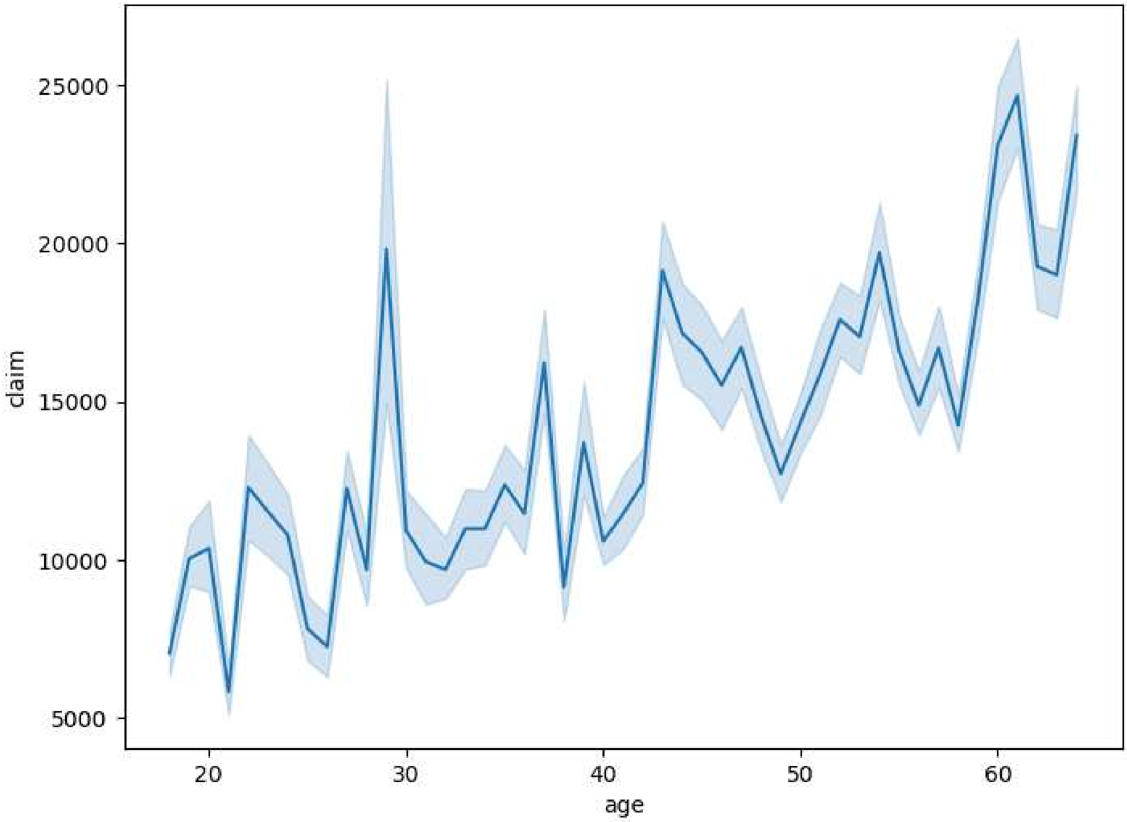


Insight

- Patients with normal blood pressure have higher average claim amounts compared to those with elevated blood pressure, potentially indicating greater utilization of healthcare services.
- The trend may be influenced by the larger number of patients in the "normal" category, which could skew the average claim amounts across categories.

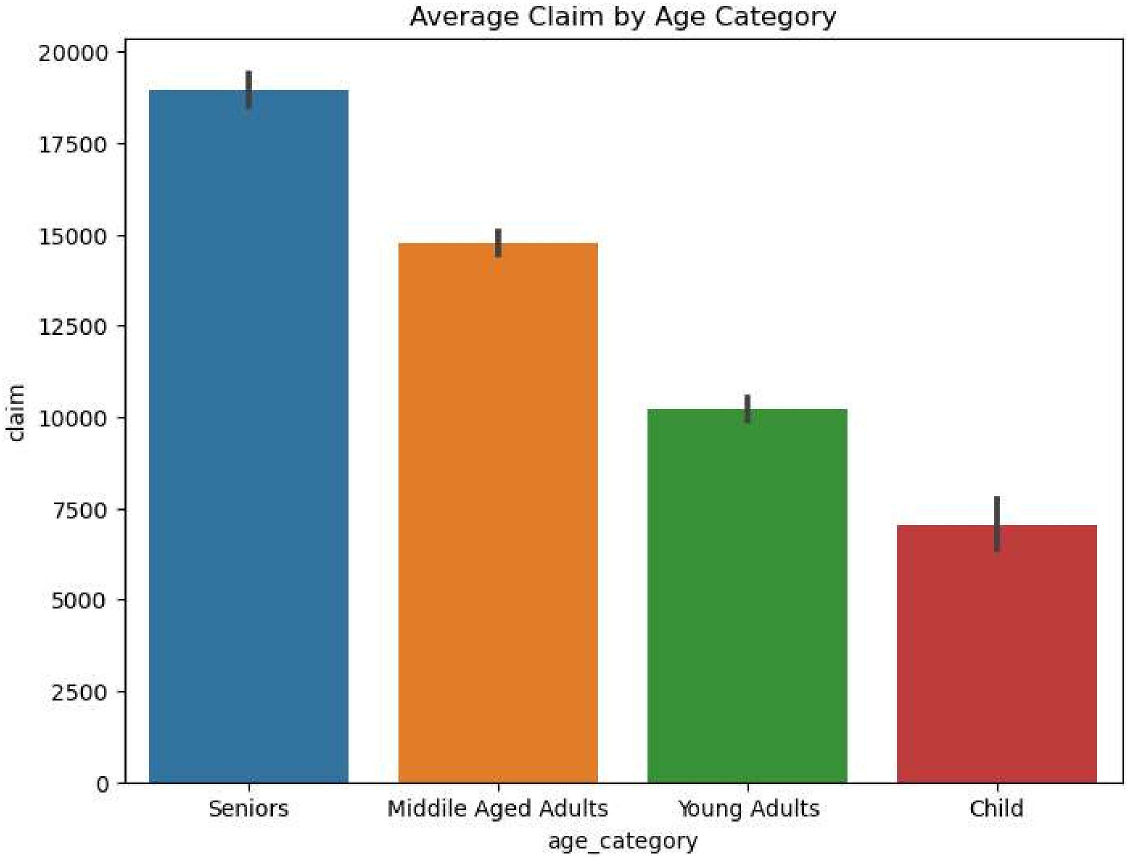
Age and Claim

In [28]:
```
plt.figure(figsize = (8,6))
sns.lineplot(x = 'age', y = 'claim', data = df)
plt.show()
```



In [29]:
```
def age_category_function(age):
    if pd.isna(age):
        return 'Unknown'
    elif age <= 18:
        return 'Child'
    elif 19 <= age <= 35:
        return 'Young Adults'
    elif 35<= age <=55:
        return 'Middile Aged Adults'
    else:
        return 'Seniors'

df['age_category'] = df['age'].apply(age_category_function)
```

In [30]:
```
plt.figure(figsize = (8,6))
sns.barplot(x = 'age_category', y = 'claim', data = df)
plt.title('Average Claim by Age Category')
plt.show()
```

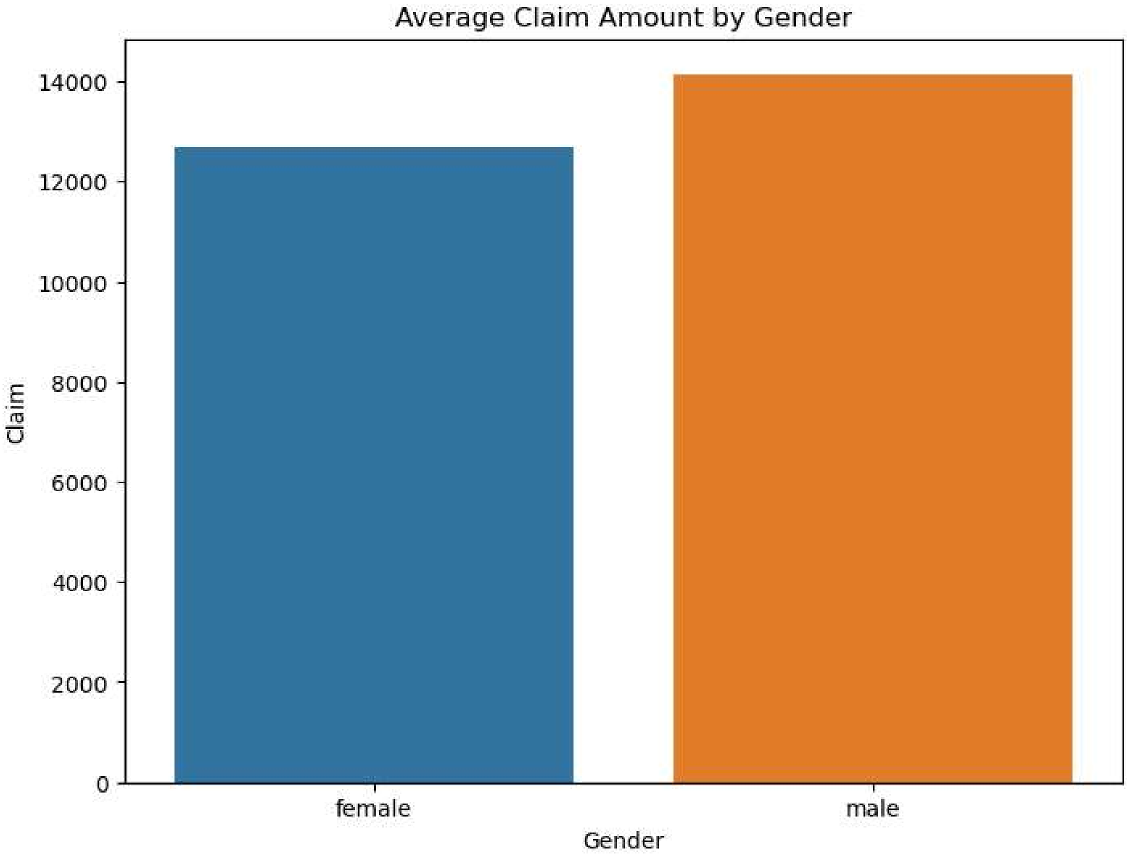


Insight

- The analysis reveals that the average claim amount is the highest among the "Seniors" age category, followed by "Middle-Aged Adults." This suggests that older individuals tend to incur higher claims, likely due to increased healthcare needs associated with aging, such as chronic conditions or greater reliance on medical services.
- The "Young Adults" and "Children" categories have lower average claims, with children having the least. This may reflect better general health and fewer medical interventions required in younger populations.

Claim Analysis by Gender

In [31]:
```
sex_claim_analysis = df.groupby('sex')['claim'].mean().reset_index()

plt.figure(figsize = (8,6))
sns.barplot(x = 'sex', y = 'claim', data = sex_claim_analysis)
plt.title('Average Claim Amount by Gender')
plt.xlabel('Gender')
plt.ylabel('Claim')
plt.show()
```

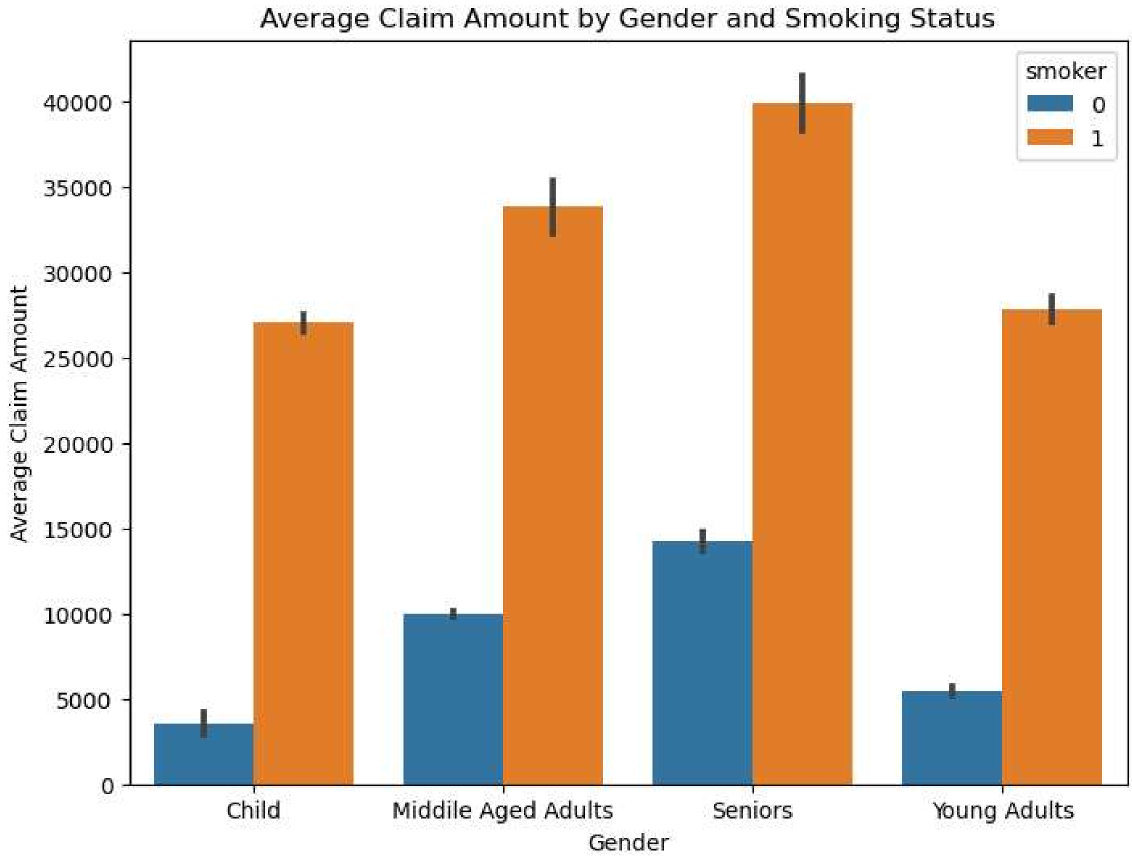


Insight

- Males show a slightly higher average claim amount than females, indicating possible gender-based differences in healthcare utilization or risk profiles.
- The variation, while minor, may stem from gender-specific health needs or conditions.

Average Claim Amount by Gender and Smoking Status

In [32]:
```
# Group the data by 'sex' and 'smoker', then calculate the mean claim
sex_smoker_claim_analysis = df.groupby(['sex', 'smoker', 'age_category'])['

# Plotting the bar plot
plt.figure(figsize = (8,6))
sns.barplot(x = 'age_category', y = 'claim', hue = 'smoker', data = sex_smo
plt.title('Average Claim Amount by Gender and Smoking Status')
plt.xlabel('Gender')
plt.ylabel('Average Claim Amount')
plt.show()
```



Insights

- Smokers consistently exhibit significantly higher claim amounts across all age categories, indicating the substantial impact of smoking on healthcare costs.
- Senior smokers display the highest average claim amount, reflecting the compounding health risks associated with age and smoking habits. Non-smokers maintain lower claims overall, reinforcing the health and financial benefits of avoiding smoking.

Random Forest Regression to Predict Insurance Claims

In [33]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor

x = df[['age', 'bmi','weight', 'smoker', 'bloodpressure', 'diabetes']]
y = df['claim']

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2,

model = RandomForestRegressor(n_estimators = 100, random_state = 42 )

model.fit(x_train, y_train)

def preddict_claim (age, bmi, weight, smoker, bloodpressure, diabetes):
    input_data = pd.DataFrame({
        'age' :[age],
        'bmi' :[bmi],
        'weight':[weight],
        'smoker':[smoker],
        'bloodpressure':[bloodpressure],
        'diabetes':[diabetes]

    })

    prediction = model.predict(input_data)

    return prediction[0]
```

As the data is non-linear, Random Forest Regression is used to create a model that can predict the claim amount of a person based on different factors such as age, BMI, weight, smoking status, blood pressure, and diabetes.

User Input-Based Claim Report

In [34]:

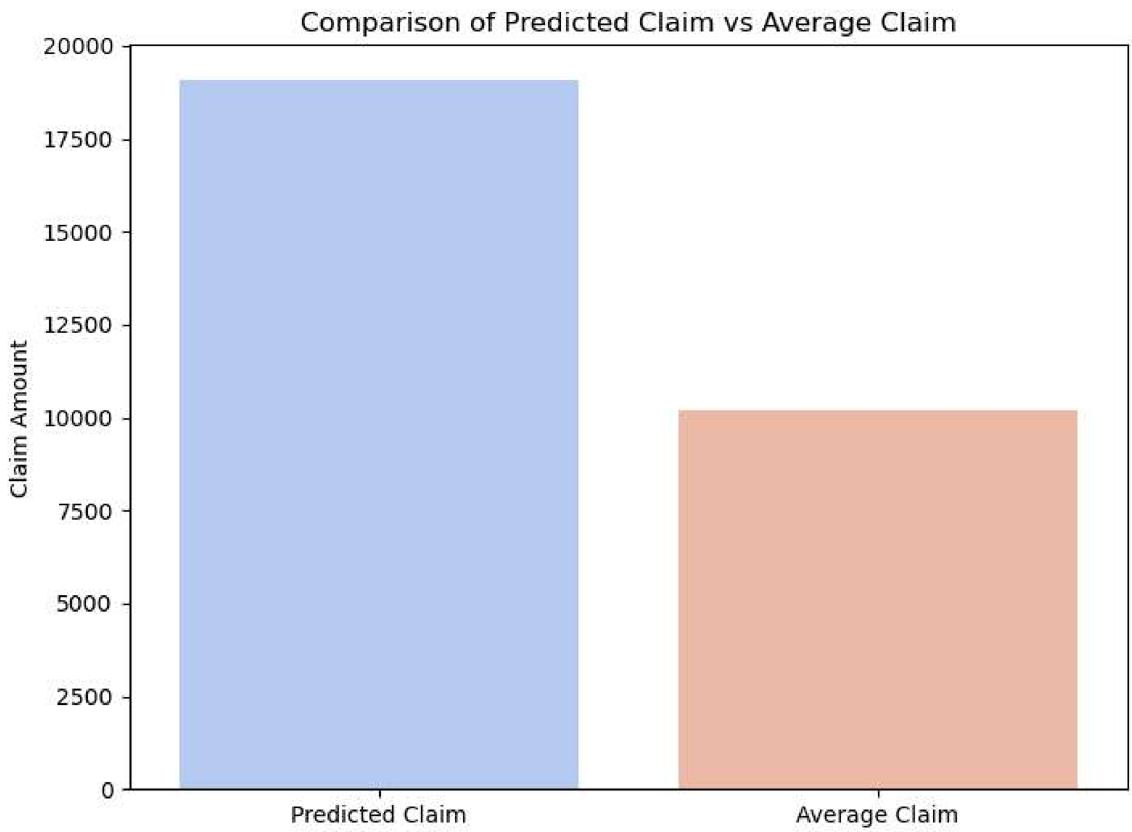
```
def predict_claim_with_report(age, bmi, weight, smoker, bloodpressure, diab

    input_data = pd.DataFrame({
        'age': [age],
        'bmi': [bmi],
        'weight': [weight],
        'smoker': [smoker],
        'bloodpressure': [bloodpressure],
        'diabetes': [diabetes]
    })


    predicted_claim = model.predict(input_data)[0]


    age_category = age_category_function(age)
    bmi_category = bmi_category_function(bmi)
    bp_category = bp_category_function(bloodpressure)


    average_claim_age = df[df['age_category'] == age_category]['claim'].mea

    print("\n\n\033[1mReport of the Person:\033[0m")
    print("=" * 40)

    report = {
        "User Age": age,
        "BMI": bmi,
        "Weight": weight,
        "Smoker Status": "Yes" if smoker == 1 else "No",
        "Blood Pressure": bloodpressure,
        "Diabetes Status": "Yes" if diabetes == 1 else "No",
        "Age Category": age_category,
        "BMI Category": bmi_category,
        "Blood Pressure Category": bp_category,
        "Predicted Claim": round(predicted_claim, 2),
        "Average Claim in Age Category": round(average_claim_age, 2),
        "Premium Suggestion": "The predicted claim is higher than the avera
    }


    for key, value in report.items():
        print(f"{key}: {value}")


    plt.figure(figsize=(8, 6))
    sns.barplot(x=['Predicted Claim', 'Average Claim'], y=[predicted_claim,
    plt.title('Comparison of Predicted Claim vs Average Claim')
    plt.ylabel('Claim Amount')
    plt.show()


age = float(input("Enter Age: "))
weight = float(input("Enter Weight (kg): "))
bmi = float(input("Enter BMI: "))
bloodpressure = float(input("Enter Blood Pressure: "))
diabetes = int(input("Enter 1 if Diabetes is present, 0 otherwise: "))
smoker = int(input("Enter 1 if Smoker, 0 otherwise: "))
```

```
predict_claim_with_report(age, bmi, weight, smoker, bloodpressure, diabetes
```

```
Enter Age: 25
Enter Weight (kg): 50
Enter BMI: 30
Enter Blood Pressure: 88
Enter 1 if Diabetes is present, 0 otherwise: 1
Enter 1 if Smoker, 0 otherwise: 1
```

Report of the Person:

```
========================================
User Age: 25.0
BMI: 30.0
Weight: 50.0
Smoker Status: Yes
Blood Pressure: 88.0
Diabetes Status: Yes
Age Category: Young Adults
BMI Category: Obese
Blood Pressure Category: Normal
Predicted Claim: 19074.31
Average Claim in Age Category: 10199.99
Premium Suggestion: The predicted claim is higher than the average claim f
or this age category. Charging a premium may be considered.
```



This model generates a personalized claim prediction based on user inputs such as age, BMI, weight, smoking status, blood pressure, and diabetes. It provides a detailed report comparing the predicted claim with the average claim for similar categories. A visual bar graph highlights the difference between the predicted and average claim amounts

Conclusion

This project successfully analyzed healthcare claim data to uncover key factors influencing claim amounts, such as BMI, smoking status, and diabetes. A Random Forest Regression model was developed to predict claim amounts based on user inputs, enabling personalized claim estimation. The model's ability to provide detailed user-specific reports ensures practical applications for insurance decision-making. Through this analysis, valuable insights were derived to better understand healthcare costs and their drivers, offering data-driven solutions for managing insurance claims effectively.

Future Scope

The project can be enhanced by incorporating additional features such as geographical location, medical history, and healthcare service utilization to improve predictive capabilities. More advanced models, like Gradient Boosting or Neural Networks, can be explored to further increase accuracy. Developing an interactive user interface would make the model accessible to non-technical users, allowing for real-world integration in insurance workflows. Future analysis could focus on time-series trends in claim amounts to enable better cost forecasting and resource allocation. These enhancements will extend the applicability of the project and contribute to more effective healthcare cost management.

In [45]:
```
from IPython.display import FileLink

# Save the DataFrame to a CSV file
df.to_csv("Healthcare_Data.csv", index=False)

# Create a download link
FileLink("Healthcare_Data.csv")
```

Out[45]: Healthcare_Data.csv (Healthcare_Data.csv)

In [48]:
```
from IPython.display import FileLink


df.to_excel("Healthcare_Data.xlsx", index = False)
FileLink("Healthcare_Data.xlsx")
```

Out[48]: Healthcare_Data.xlsx (Healthcare_Data.xlsx)

In [ ]:

In [ ]: