21BDS0379

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EDA THEORY- D1

GITHUB LINK: https://github.com/shreyashax/21BDS0379_EDA_Theory_DA/tree/main

DATASET NAME: student-mat.csv

DATASET LINK: https://raw.githubusercontent.com/salemprakash/EDA/main/Data/stud mat.csv

Digital Assignment 1

PHASE 1

Module 2

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

In [2]:
```
# Load dataset
df = pd.read_csv('MyDataset_EDA.csv')
```

In [3]:
```
# Display basic info
df.info()
print("\nSummary Statistics:")
print(df.describe(include='all'))
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 395 entries, 0 to 394
Data columns (total 33 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   school      395 non-null    object
 1   sex         393 non-null    object
 2   age         395 non-null    int64 
 3   address     394 non-null    object
 4   famsize     394 non-null    object
 5   Pstatus     395 non-null    object
 6   Medu        395 non-null    int64 
 7   Fedu        395 non-null    int64 
 8   Mjob        395 non-null    object
 9   Fjob        395 non-null    object
 10  reason      395 non-null    object
 11  guardian    395 non-null    object
 12  traveltime  395 non-null    int64 
 13  studytime   395 non-null    int64 
 14  failures    395 non-null    int64 
 15  schoolsup   393 non-null    object
 16  famsup      395 non-null    object
 17  paid        395 non-null    object
 18  activities  395 non-null    object
 19  nursery     395 non-null    object
 20  higher      395 non-null    object
 21  internet    395 non-null    object
 22  romantic    395 non-null    object
 23  famrel      395 non-null    int64 
 24  freetime    395 non-null    int64 
 25  goout       395 non-null    int64 
 26  Dalc        395 non-null    int64 
 27  Walc        395 non-null    int64 
 28  health      395 non-null    int64 
 29  absences    395 non-null    int64 
 30  G1          395 non-null    int64 
 31  G2          395 non-null    int64 
 32  G3          395 non-null    int64 
dtypes: int64(16), object(17)
memory usage: 102.0+ KB

Summary Statistics:
       school  sex         age address famsize Pstatus        Medu  \
count     395  393  395.000000     394     394     395  395.000000   
unique      2    2         NaN       3       2       3         NaN   
top        GP    F         NaN       U     GT3       T         NaN   
freq      349  208         NaN     304     280     348         NaN   
mean      NaN  NaN   16.696203     NaN     NaN     NaN    2.749367   
std       NaN  NaN    1.276043     NaN     NaN     NaN    1.094735   
min       NaN  NaN   15.000000     NaN     NaN     NaN    0.000000   
25%       NaN  NaN   16.000000     NaN     NaN     NaN    2.000000   
50%       NaN  NaN   17.000000     NaN     NaN     NaN    3.000000   
75%       NaN  NaN   18.000000     NaN     NaN     NaN    4.000000   
max       NaN  NaN   22.000000     NaN     NaN     NaN    4.000000   

              Fedu   Mjob   Fjob  ...      famrel    freetime       goout  \
count   395.000000    395    395  ...  395.000000  395.000000  395.000000   
unique         NaN      5      5  ...         NaN         NaN         NaN   
top            NaN  other  other  ...         NaN         NaN         NaN   
freq           NaN    141    217  ...         NaN         NaN         NaN   
mean      2.521519    NaN    NaN  ...    3.944304    3.235443    3.108861   
std       1.088201    NaN    NaN  ...    0.896659    0.998862    1.113278   
min       0.000000    NaN    NaN  ...    1.000000    1.000000    1.000000   
25%       2.000000    NaN    NaN  ...    4.000000    3.000000    2.000000   
50%       2.000000    NaN    NaN  ...    4.000000    3.000000    3.000000   
75%       3.000000    NaN    NaN  ...    5.000000    4.000000    4.000000   
max       4.000000    NaN    NaN  ...    5.000000    5.000000    5.000000   
```

```
              Dalc        Walc      health    absences          G1  \
count   395.000000  395.000000  395.000000  395.000000  395.000000
unique         NaN         NaN         NaN         NaN         NaN
top            NaN         NaN         NaN         NaN         NaN
freq           NaN         NaN         NaN         NaN         NaN
mean      1.481013    2.291139    3.554430    5.708861   10.908861
std       0.890741    1.287897    1.390303    8.003096    3.319195
min       1.000000    1.000000    1.000000    0.000000    3.000000
25%       1.000000    1.000000    3.000000    0.000000    8.000000
50%       1.000000    2.000000    4.000000    4.000000   11.000000
75%       2.000000    3.000000    5.000000    8.000000   13.000000
max       5.000000    5.000000    5.000000   75.000000   19.000000

                G2          G3
count   395.000000  395.000000
unique         NaN         NaN
top            NaN         NaN
freq           NaN         NaN
mean     10.713924   10.415190
std       3.761505    4.581443
min       0.000000    0.000000
25%       9.000000    8.000000
50%      11.000000   11.000000
75%      13.000000   14.000000
max      19.000000   20.000000

[11 rows x 33 columns]
```

In [4]:
```python
# Handling missing values
df['sex'].fillna(df['sex'].mode()[0], inplace=True)
df['address'].fillna(df['address'].mode()[0], inplace=True)
df['famsize'].fillna(df['famsize'].mode()[0], inplace=True)
df['schoolsup'].fillna(df['schoolsup'].mode()[0], inplace=True)
```

In [5]:
```python
# Remove duplicate rows
df = df.drop_duplicates()
```

In [6]:
```python
# Convert data types if needed
def convert_dtype(df):
    for col in df.columns:
        if df[col].dtype == 'object':
            try:
                df[col] = pd.to_datetime(df[col])  # Convert date-like columns
            except:
                pass  # If conversion fails, leave as object
        elif df[col].dtype in ['int64', 'float64']:
            df[col] = pd.to_numeric(df[col], errors='coerce')  # Convert numeric values
    return df

df = convert_dtype(df)
```

In [7]:
```python
# Handling outliers (Removing values beyond 1.5*IQR)
def remove_outliers(df):
    for col in ['absences']:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        df = df[(df[col] >= lower_bound) & (df[col] <= upper_bound)]
    return df

df = remove_outliers(df)
```

In [8]:
```
# Encoding categorical variables
for col in df.select_dtypes(include=['object']).columns:
    df[col] = df[col].astype('category').cat.codes
```

Module 3

Univariate Analysis

In [9]:
```
data = pd.read_csv('MyDataset_EDA.csv')
# Central Tendency Measures
for col in df.select_dtypes(include=['float64', 'int64']).columns:
    print(f"\n{col}:")
    print(f"Mean: {df[col].mean()}")
    print(f"Median: {df[col].median()}")
    print(f"Mode: {df[col].mode()[0]}")

# Dispersion Measures
for col in df.select_dtypes(include=['float64', 'int64']).columns:
    print(f"\n{col}:")
    print(f"Range: {df[col].max() - df[col].min()}")
    print(f"Variance: {df[col].var()}")
    print(f"Standard Deviation: {df[col].std()}")
    print(f"Min: {df[col].min()}")
    print(f"Max: {df[col].max()}")
    print(f"Q1: {df[col].quantile(0.25)}")
    print(f"Q3: {df[col].quantile(0.75)}")
    print(f"IQR: {df[col].quantile(0.75) - df[col].quantile(0.25)}")
```

```
age:
Mean: 16.67105263157895
Median: 17.0
Mode: 16

Medu:
Mean: 2.7263157894736842
Median: 3.0
Mode: 4

Fedu:
Mean: 2.5078947368421054
Median: 2.0
Mode: 2

traveltime:
Mean: 1.444736842105263
Median: 1.0
Mode: 1

studytime:
Mean: 2.042105263157895
Median: 2.0
Mode: 2

failures:
Mean: 0.3263157894736842
Median: 0.0
Mode: 0

famrel:
Mean: 3.9473684210526314
Median: 4.0
Mode: 4

freetime:
Mean: 3.2605263157894737
Median: 3.0
Mode: 3

goout:
Mean: 3.107894736842105
Median: 3.0
Mode: 3

Dalc:
Mean: 1.481578947368421
Median: 1.0
Mode: 1

Walc:
Mean: 2.278947368421053
Median: 2.0
Mode: 1

health:
Mean: 3.5710526315789473
Median: 4.0
Mode: 5

absences:
Mean: 4.602631578947369
Median: 3.0
Mode: 0

G1:
Mean: 10.921052631578947
```

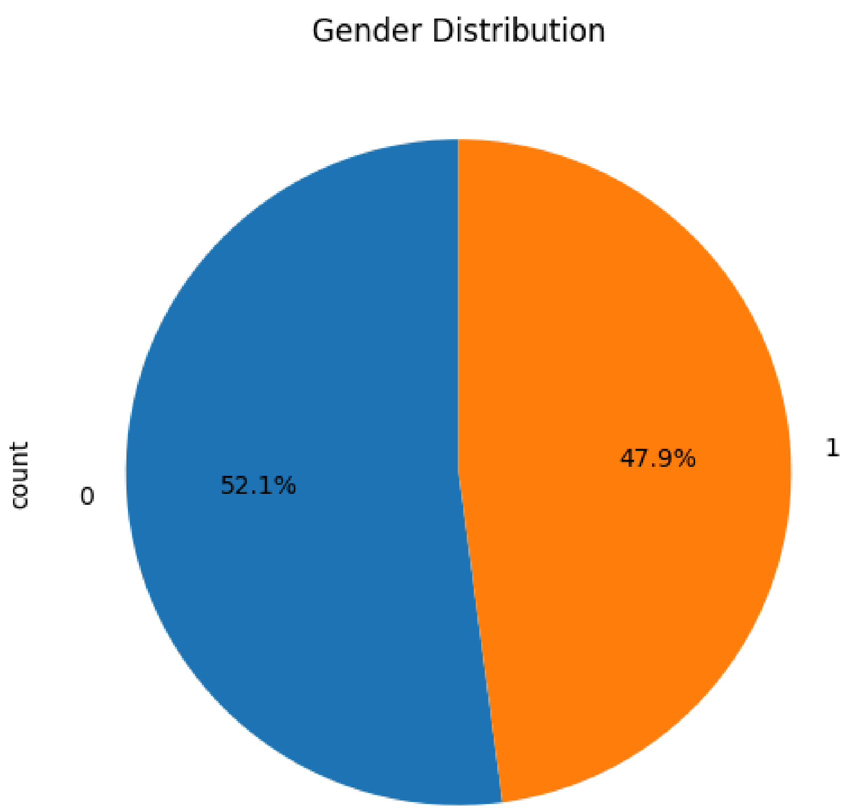
```
Median: 11.0
Mode: 10

G2:
Mean: 10.723684210526315
Median: 11.0
Mode: 9

G3:
Mean: 10.421052631578947
Median: 11.0
Mode: 10

age:
Range: 7
Variance: 1.625017358700184
Standard Deviation: 1.2747616870223955
Min: 15
Max: 22
Q1: 16.0
Q3: 18.0
IQR: 2.0

Medu:
Range: 4
Variance: 1.2124982641299888
Standard Deviation: 1.1011349890590112
Min: 0
Max: 4
Q1: 2.0
Q3: 4.0
IQR: 2.0

Fedu:
Range: 4
Variance: 1.1951881683099506
Standard Deviation: 1.0932466182476626
Min: 0
Max: 4
Q1: 2.0
Q3: 3.0
IQR: 1.0

traveltime:
Range: 3
Variance: 0.49561866407443533
Standard Deviation: 0.7040018920957779
Min: 1
Max: 4
Q1: 1.0
Q3: 2.0
IQR: 1.0

studytime:
Range: 3
Variance: 0.7159005693653675
Standard Deviation: 0.8461090765175419
Min: 1
Max: 4
Q1: 1.0
Q3: 2.0
IQR: 1.0

failures:
Range: 3
Variance: 0.5581447021247088
Standard Deviation: 0.7470908258871265
```

```
Min: 0
Max: 3
Q1: 0.0
Q3: 0.0
IQR: 0.0

famrel:
Range: 4
Variance: 0.8204416053325941
Standard Deviation: 0.9057823167475694
Min: 1
Max: 5
Q1: 4.0
Q3: 5.0
IQR: 1.0

freetime:
Range: 4
Variance: 0.9688862657964142
Standard Deviation: 0.9843202049111937
Min: 1
Max: 5
Q1: 3.0
Q3: 4.0
IQR: 1.0

goout:
Range: 4
Variance: 1.2363491181780284
Standard Deviation: 1.1119123698286788
Min: 1
Max: 5
Q1: 2.0
Q3: 4.0
IQR: 2.0

Dalc:
Range: 4
Variance: 0.8096861547007312
Standard Deviation: 0.8998256246077522
Min: 1
Max: 5
Q1: 1.0
Q3: 2.0
IQR: 1.0

Walc:
Range: 4
Variance: 1.663407860019446
Standard Deviation: 1.2897317007887517
Min: 1
Max: 5
Q1: 1.0
Q3: 3.0
IQR: 2.0

health:
Range: 4
Variance: 1.90786696292181
Standard Deviation: 1.3812555748020747
Min: 1
Max: 5
Q1: 3.0
Q3: 5.0
IQR: 2.0

absences:
```

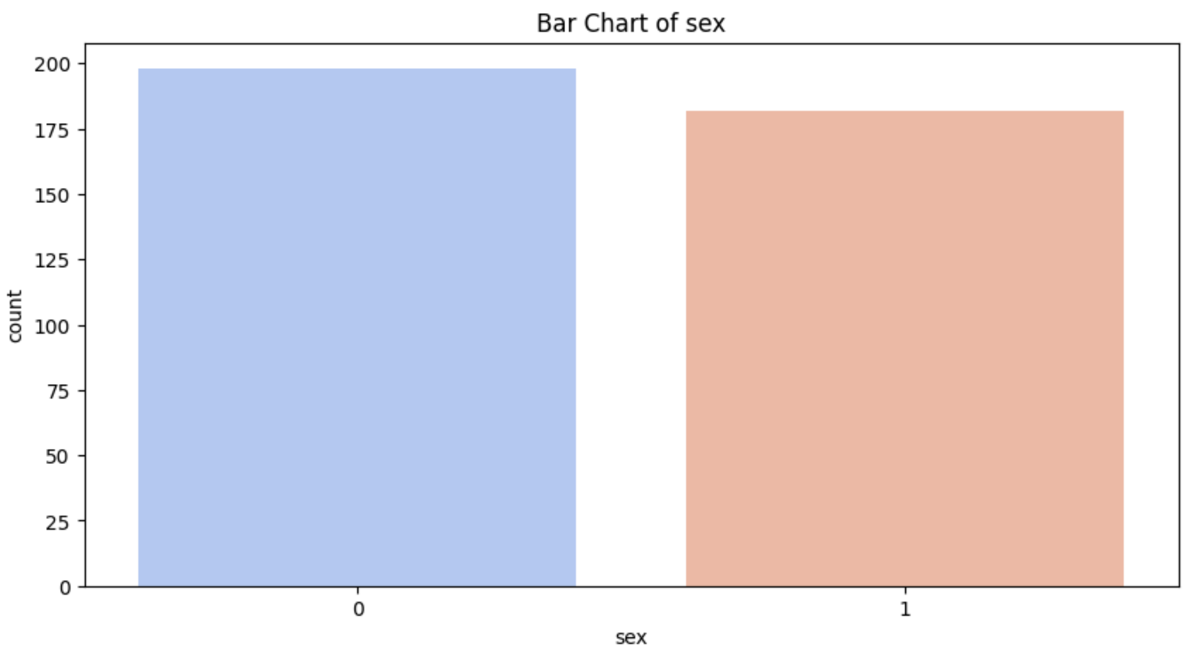
```
Range: 20
Variance: 24.683370365227063
Standard Deviation: 4.968236142256833
Min: 0
Max: 20
Q1: 0.0
Q3: 7.0
IQR: 7.0

G1:
Range: 16
Variance: 10.975281210942937
Standard Deviation: 3.3128961968258133
Min: 3
Max: 19
Q1: 8.0
Q3: 13.0
IQR: 5.0

G2:
Range: 19
Variance: 14.232155256214405
Standard Deviation: 3.772552883156763
Min: 0
Max: 19
Q1: 9.0
Q3: 13.0
IQR: 4.0

G3:
Range: 20
Variance: 21.27343424524371
Standard Deviation: 4.612313329040397
Min: 0
Max: 20
Q1: 8.0
Q3: 14.0
IQR: 6.0
```

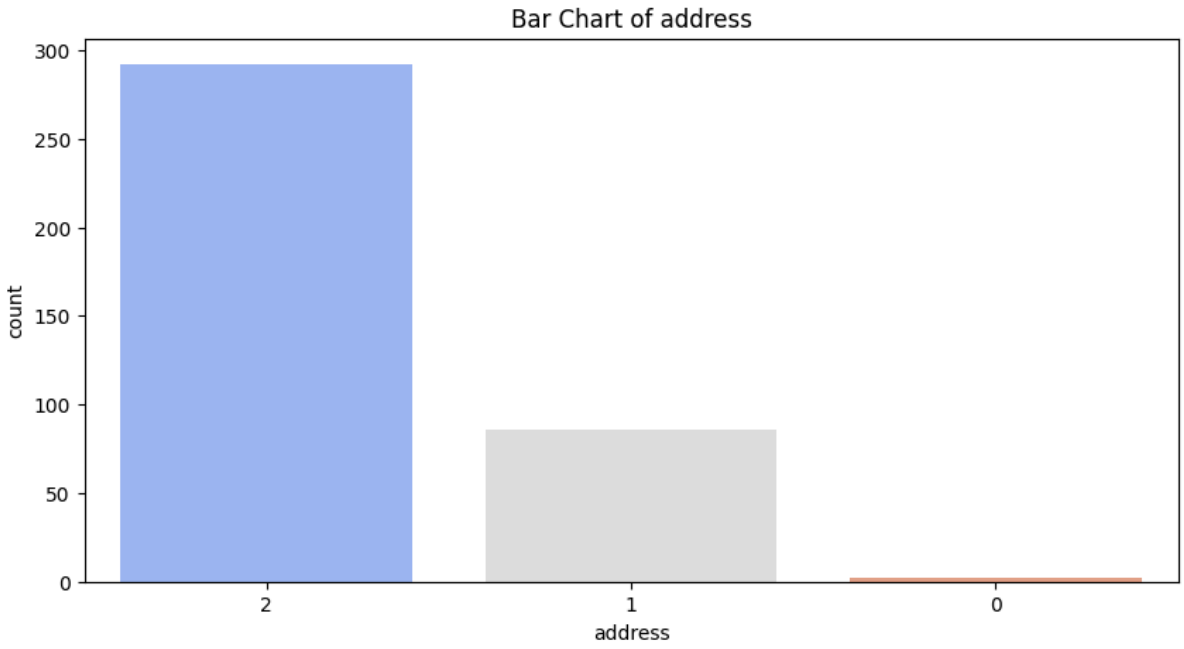
In [10]:

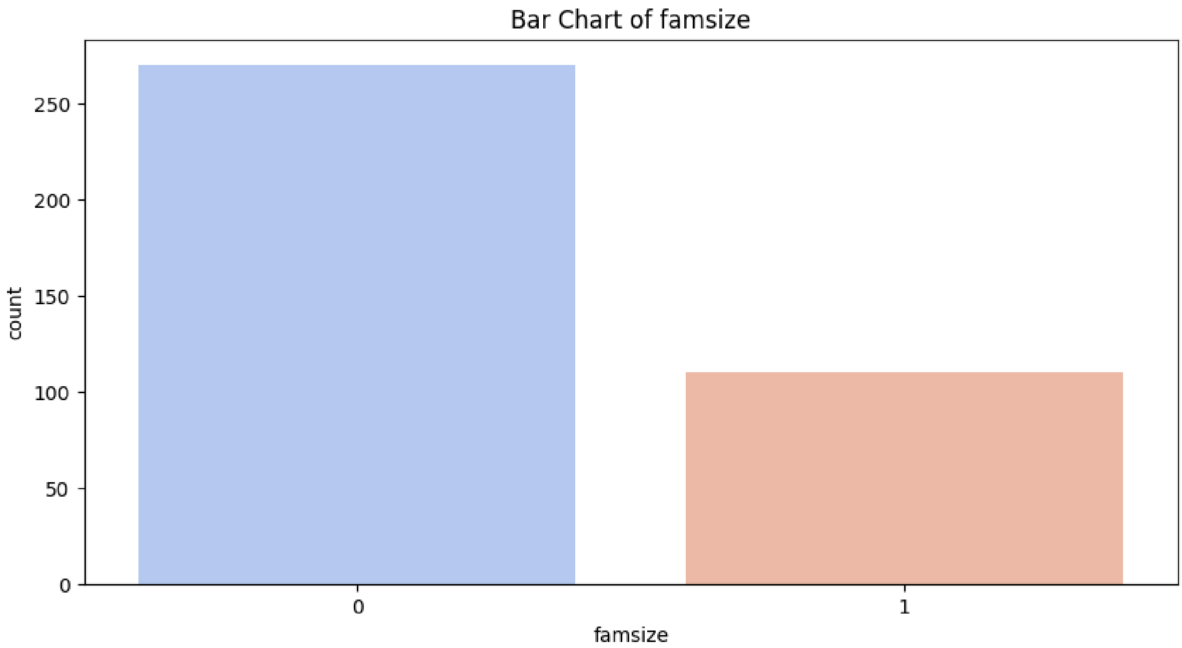
```python
# Visualization: Pie Chart of Gender distribution
plt.figure(figsize=(6,6))
df['sex'].value_counts().plot.pie(autopct='%1.1f%%', startangle=90)
plt.title("Gender Distribution")
plt.show()
```

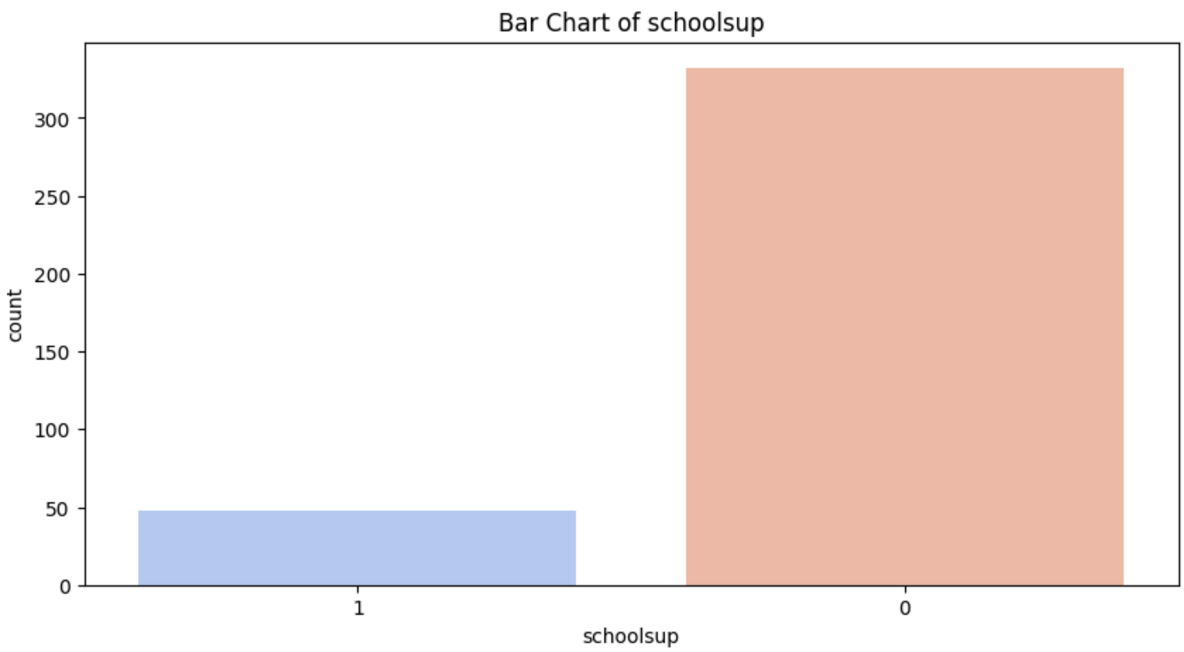


In [11]:
```
categorical_cols = ['sex', 'address', 'famsize', 'schoolsup', 'age_group']
for cat_col in categorical_cols:
    if cat_col in df.columns:
        plt.figure(figsize=(10,5))
        sns.countplot(x=df[cat_col].astype(str), palette='coolwarm')
        plt.title(f'Bar Chart of {cat_col}')
        plt.show()
    else:
        print(f"Column '{cat_col}' not found in DataFrame, skipping.")
```



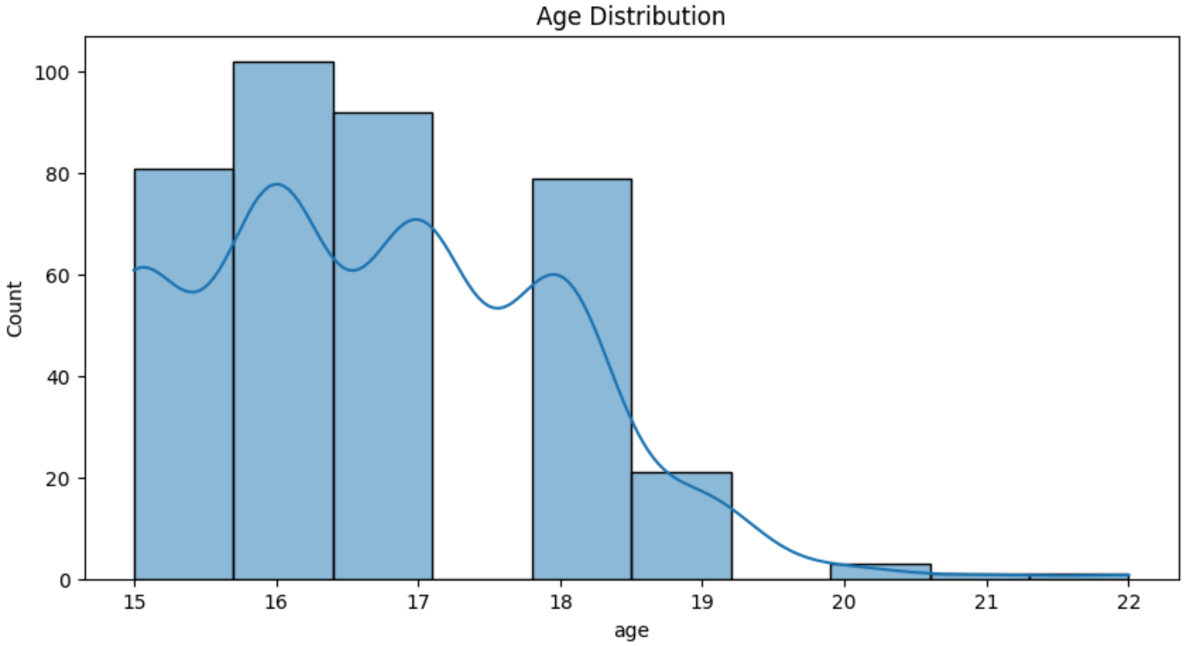

Bar Chart of address
count
0
50
100
150
200
250
300
2
1
0
address


Bar Chart of famsize
count
0
50
100
150
200
250
0
1
famsize

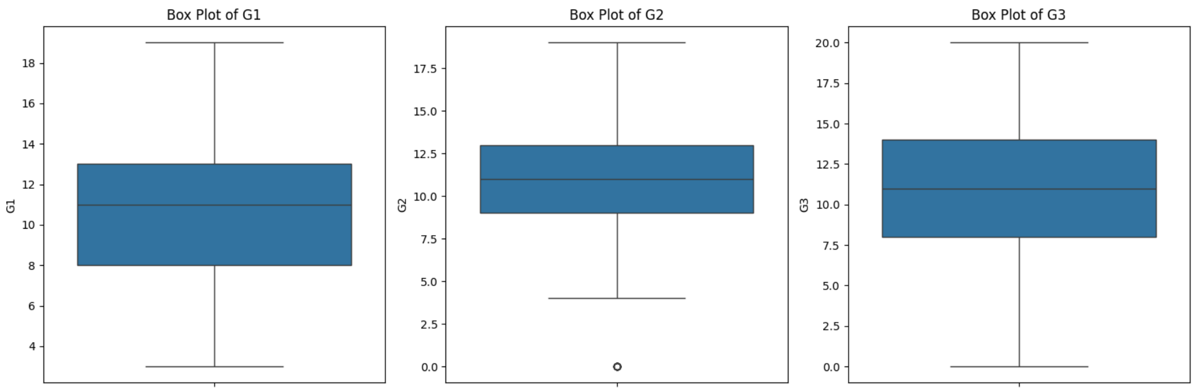

Bar Chart of schoolsup
count
0
50
100
150
200
250
300
1
0
schoolsup

```
Column 'age_group' not found in DataFrame, skipping.
```

In [12]:
```python
plt.figure(figsize=(10,5))
sns.histplot(df['age'], bins=10, kde=True)
plt.title('Age Distribution')
plt.show()
```



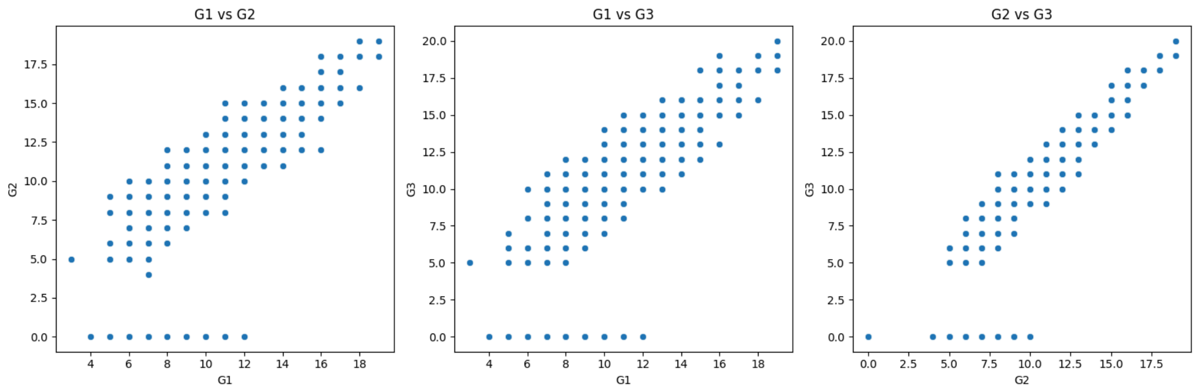
In [13]:
```python
# Select three numeric columns for boxplots (replace with your desired columns)
columns_for_boxplots = ['G1', 'G2', 'G3']

fig, axes = plt.subplots(1, 3, figsize=(15, 5))

for i, col in enumerate(columns_for_boxplots):
    sns.boxplot(y=df[col], ax=axes[i])
    axes[i].set_title(f'Box Plot of {col}')

plt.tight_layout()
plt.show()
```



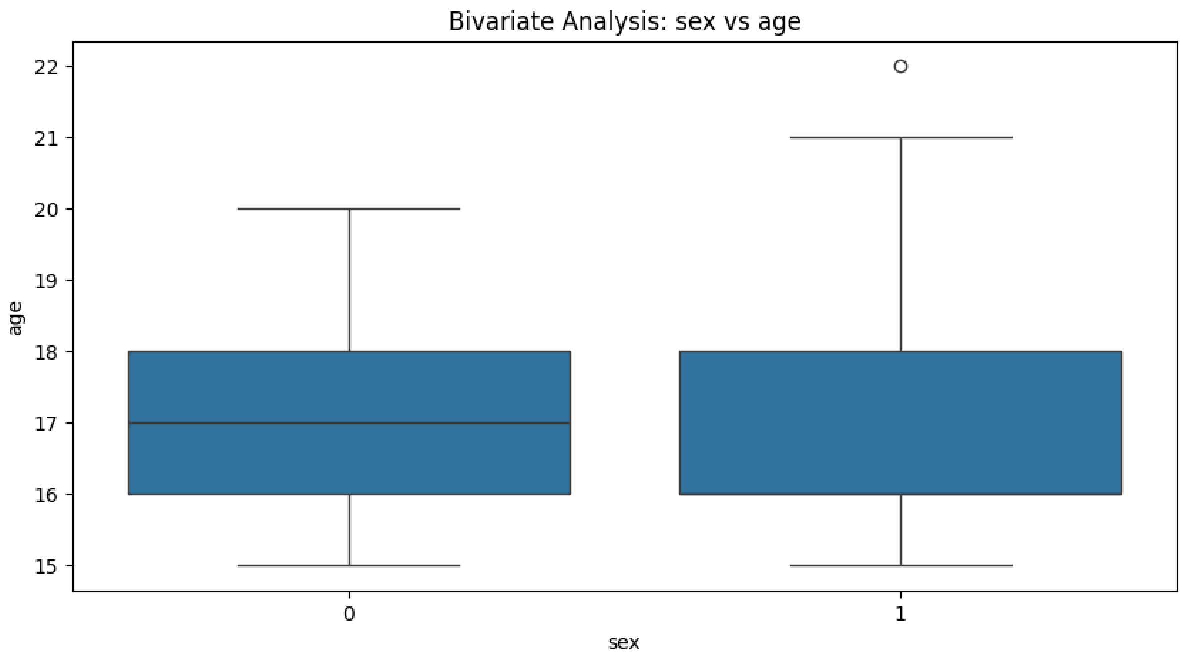
Bivariate Analysis

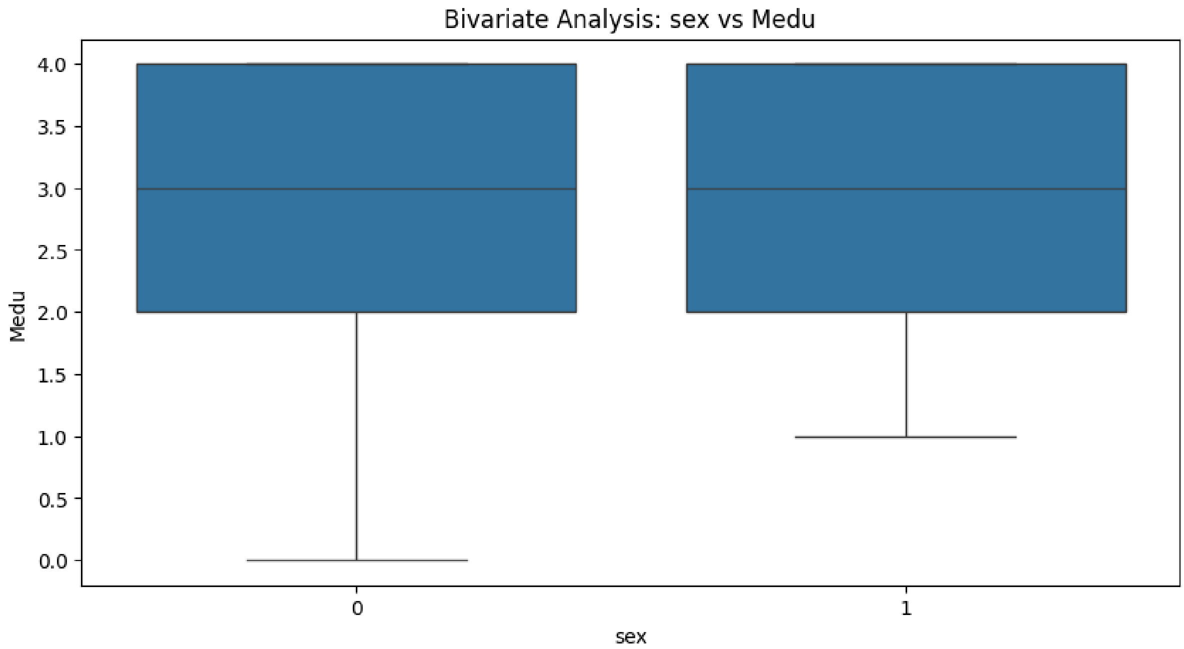
In [15]:
```python
# Create a figure and axes for subplots
fig, axes = plt.subplots(1, 3, figsize=(15, 5))

# Scatter plot: G1 vs G2
sns.scatterplot(x='G1', y='G2', data=df, ax=axes[0])
axes[0].set_title('G1 vs G2')

# Scatter plot: G1 vs G3
sns.scatterplot(x='G1', y='G3', data=df, ax=axes[1])
```

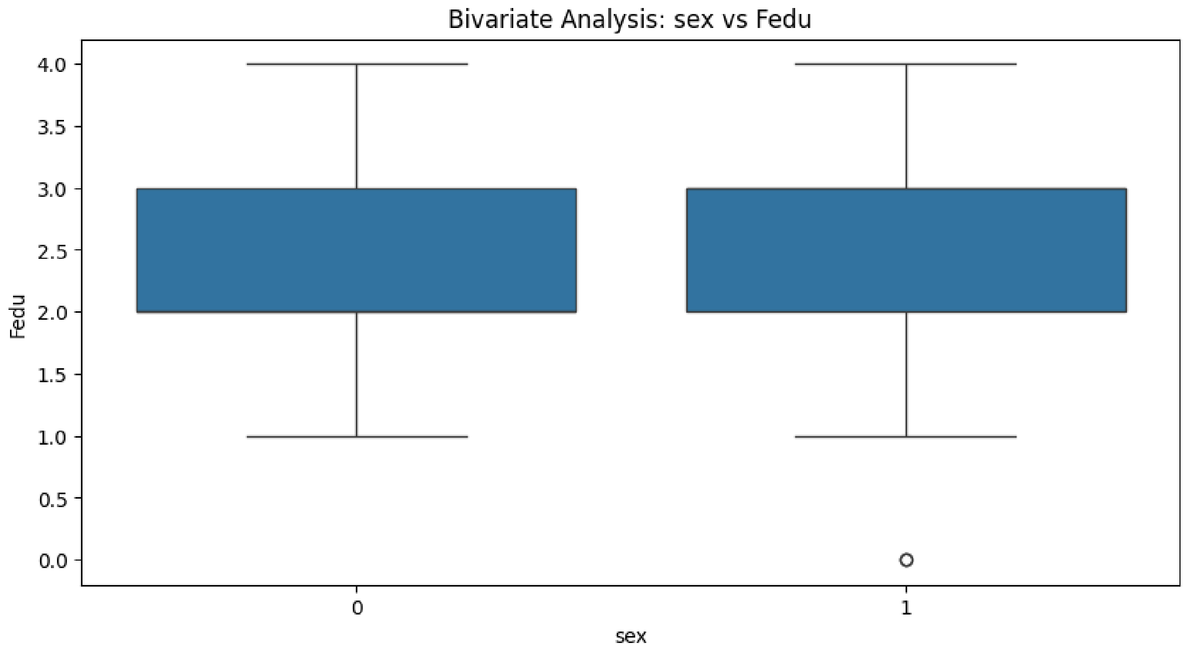
```python
axes[1].set_title('G1 vs G3')

# Scatter plot: G2 vs G3
sns.scatterplot(x='G2', y='G3', data=df, ax=axes[2])
axes[2].set_title('G2 vs G3')

plt.tight_layout()
plt.show()
```

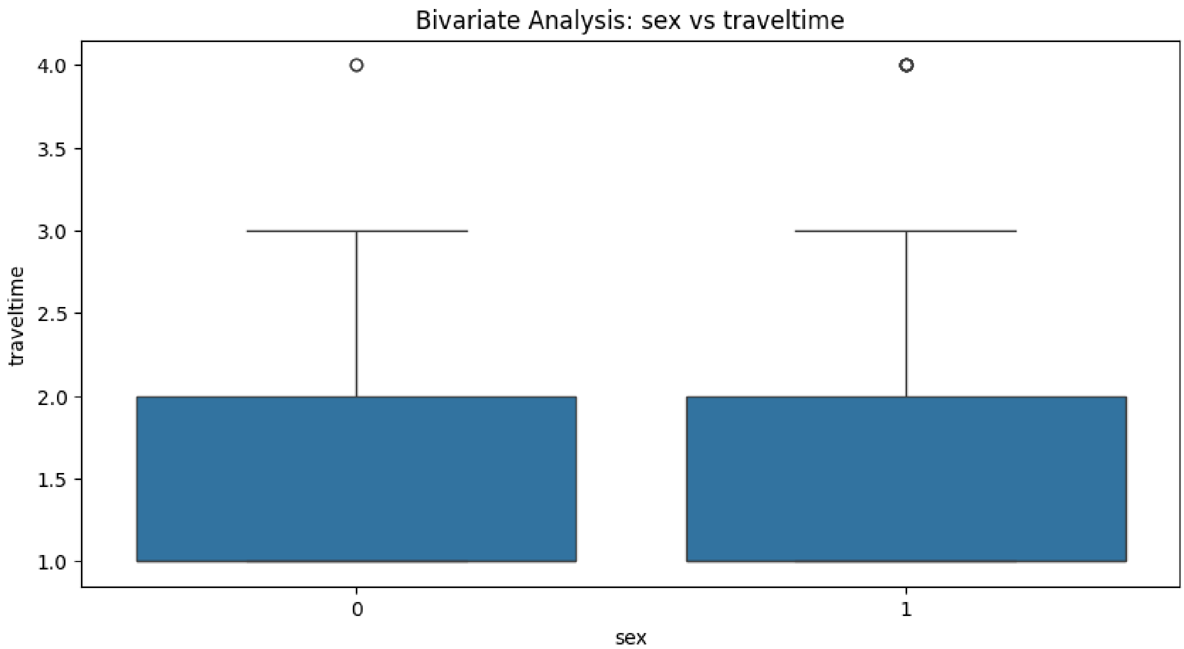


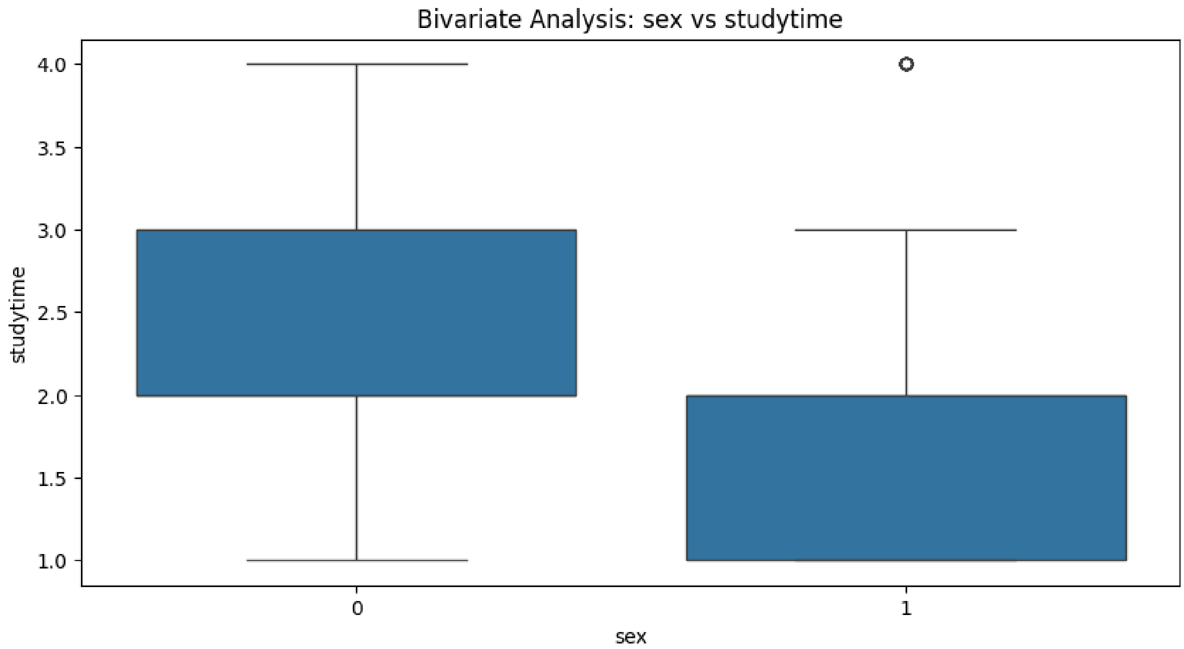
In [17]:
```python
categorical_cols = ['sex', 'address', 'famsize', 'schoolsup', 'age_group']
for cat_col in categorical_cols:
    if cat_col in df.columns:
        for num_col in df.select_dtypes(include=['float64', 'int64']).columns:
            plt.figure(figsize=(10,5))
            sns.boxplot(x=df[cat_col].astype(str), y=df[num_col])
            plt.title(f'Bivariate Analysis: {cat_col} vs {num_col}')
            plt.show()
    else:
        print(f"Column '{cat_col}' not found in DataFrame, skipping.")
```

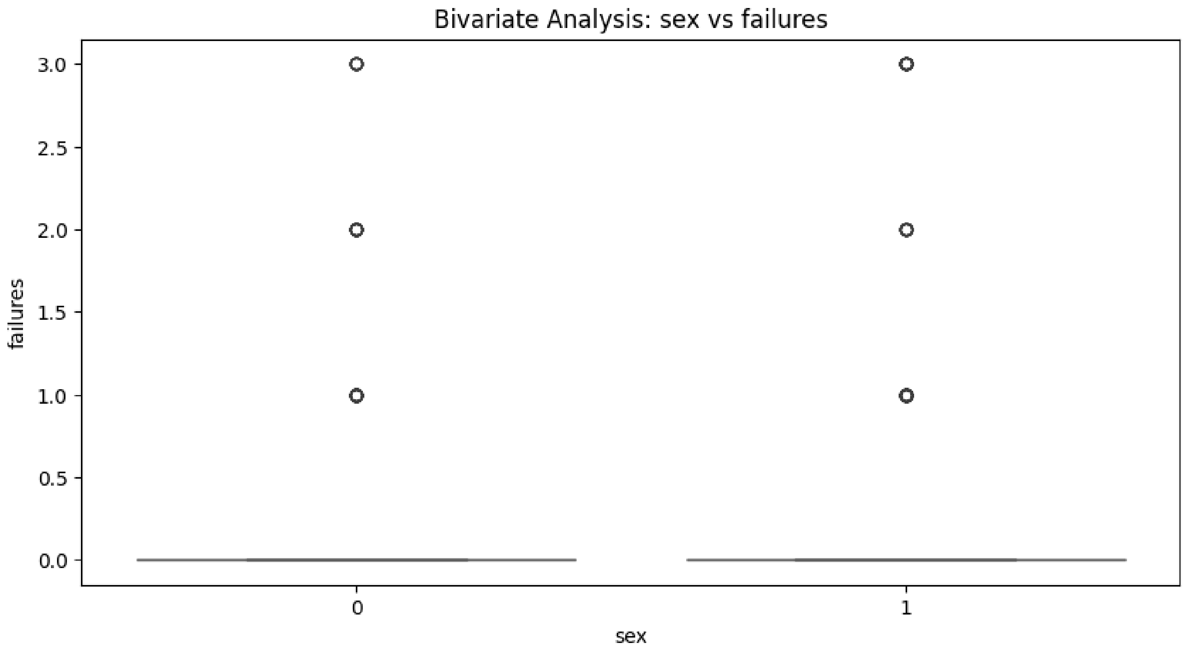


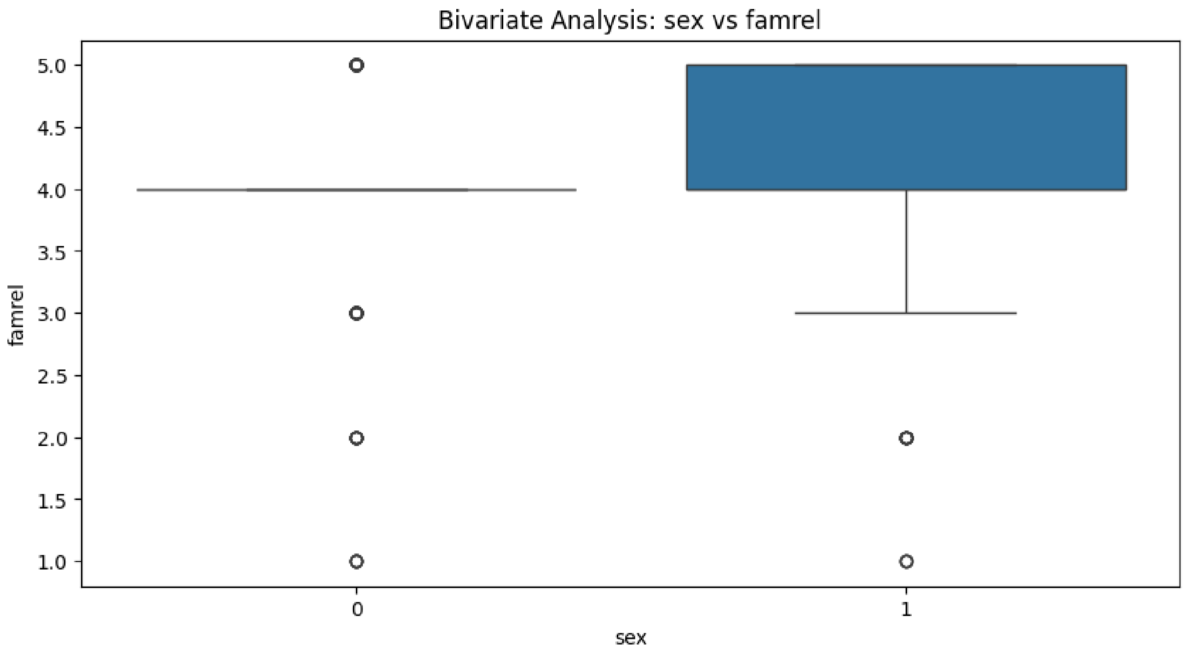

Bivariate Analysis: sex vs Medu
Medu
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
1
sex

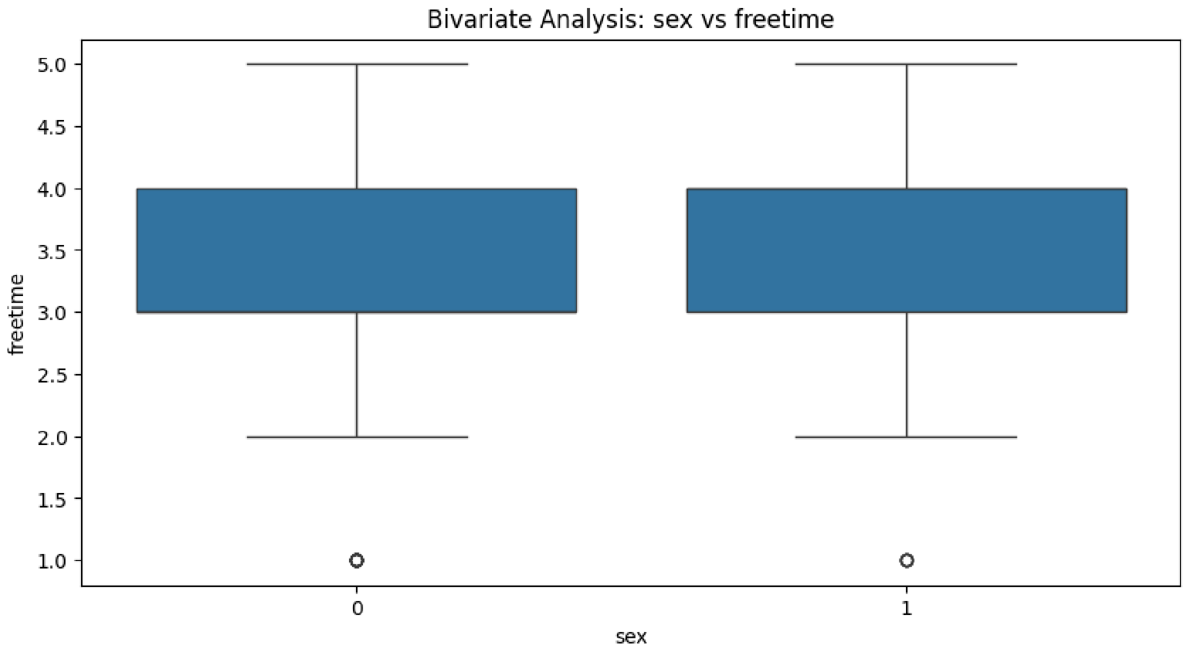

Bivariate Analysis: sex vs Fedu
Fedu
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
1
sex

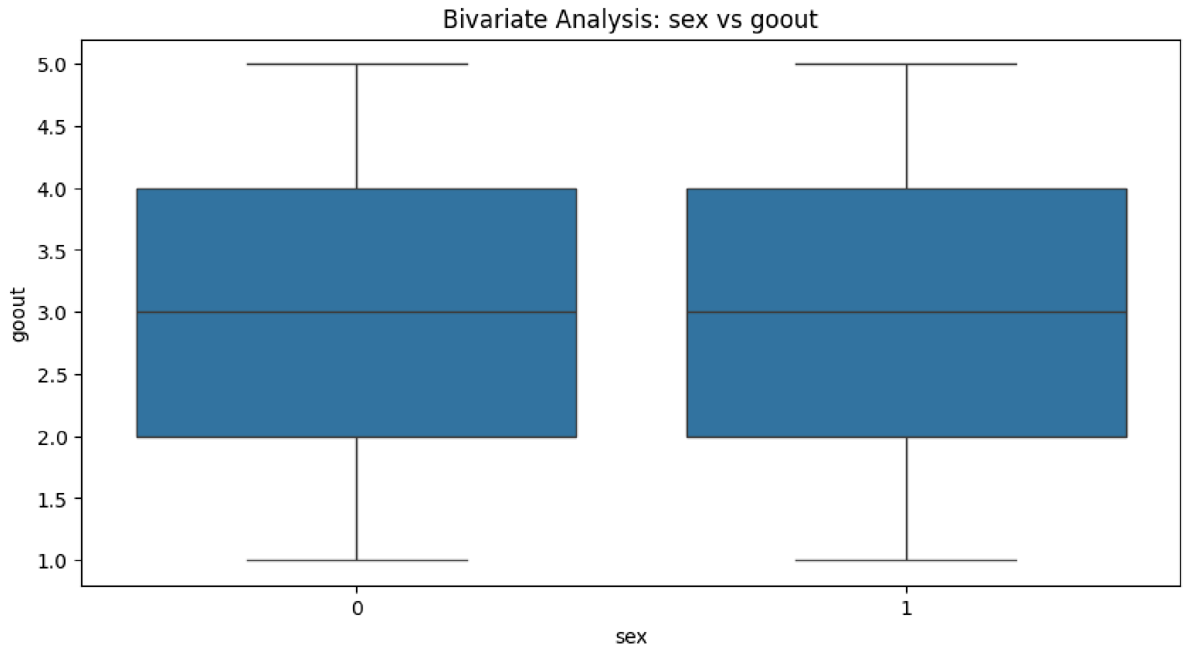

Bivariate Analysis: sex vs traveltime
traveltime
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0
1
sex

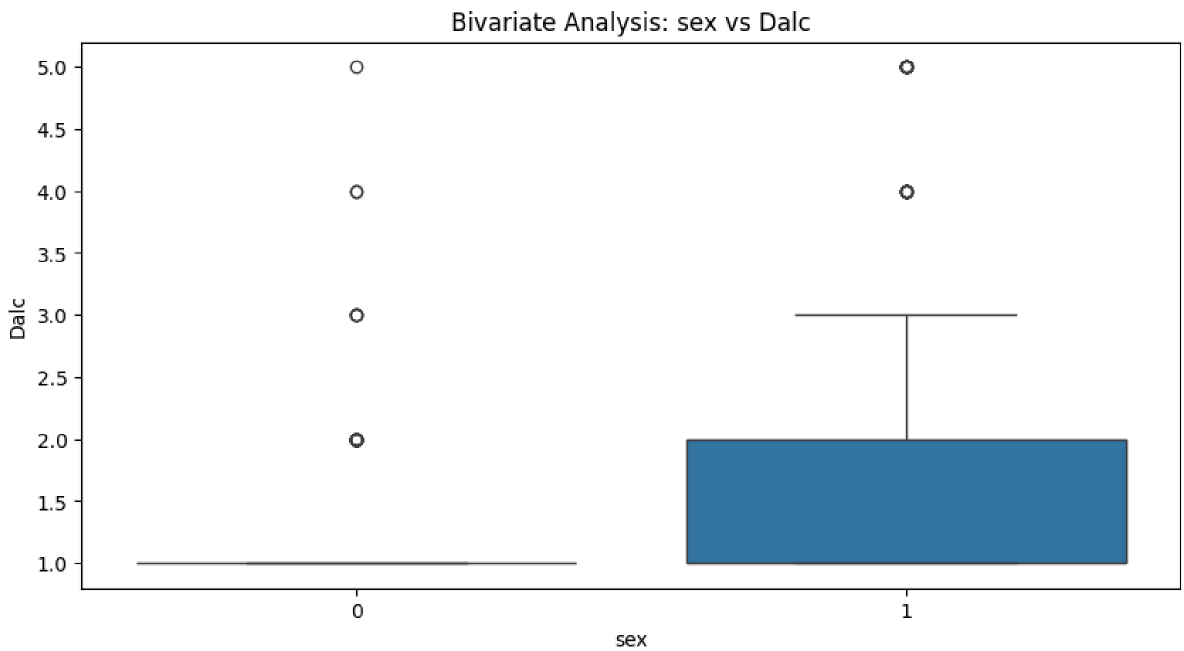

Bivariate Analysis: sex vs studytime
studytime
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0
1
sex

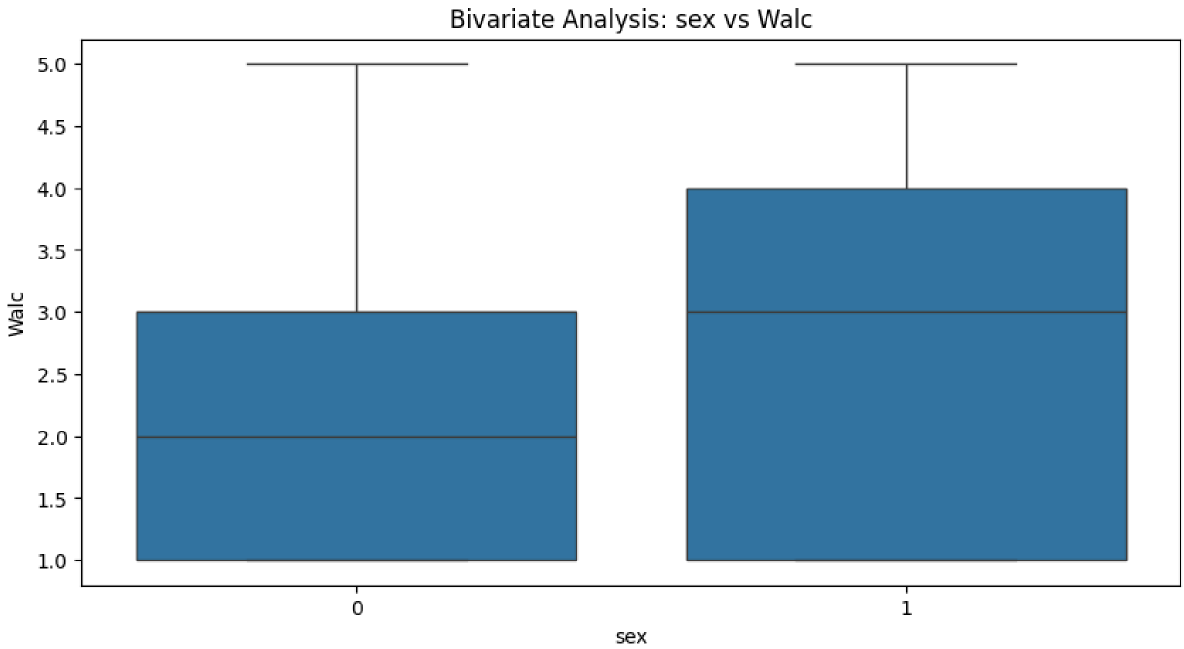

Bivariate Analysis: sex vs failures
failures
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
1
sex

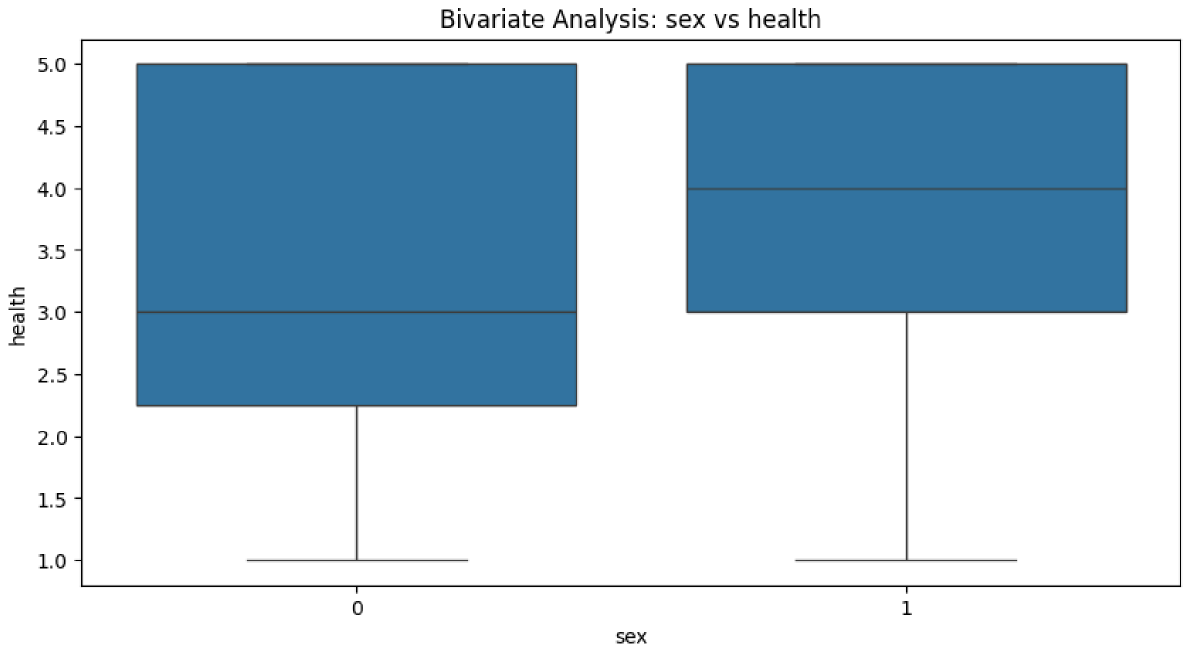

Bivariate Analysis: sex vs famrel
famrel
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0
1
sex

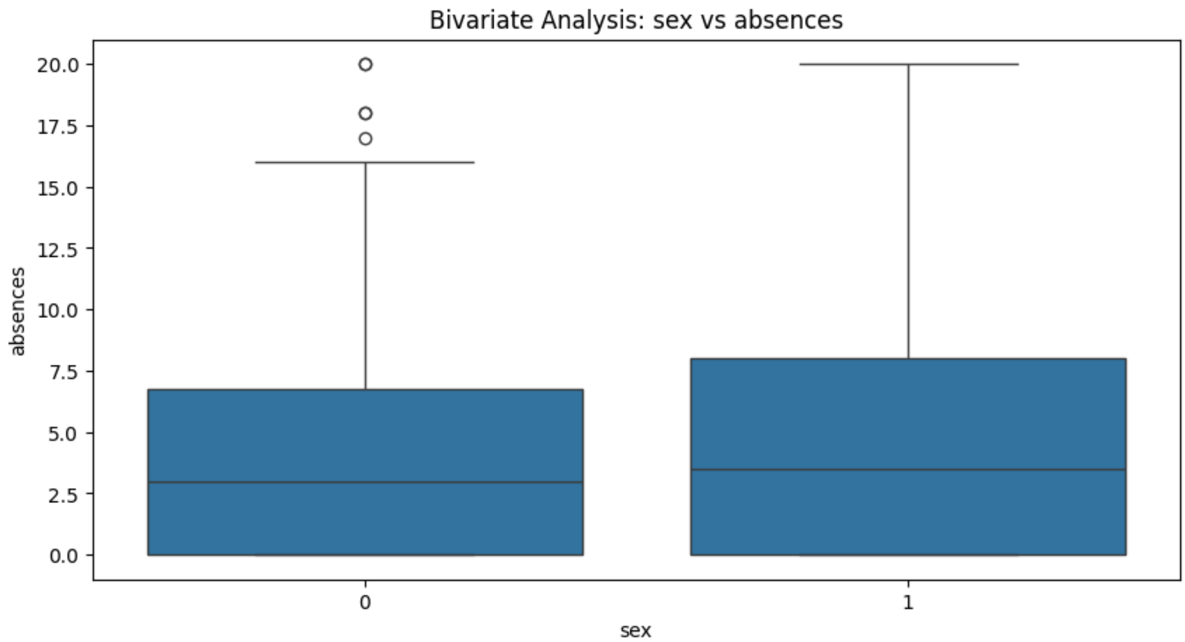

Bivariate Analysis: sex vs freetime
freetime
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0
1
sex

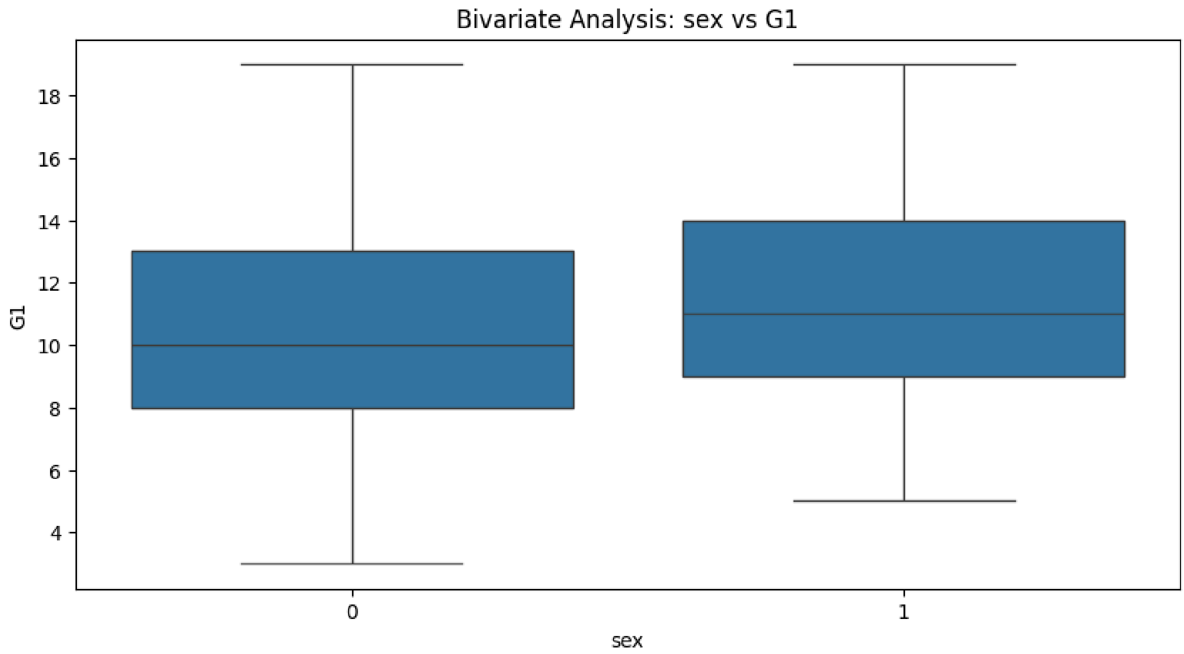

Bivariate Analysis: sex vs goout
goout
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0
1
sex

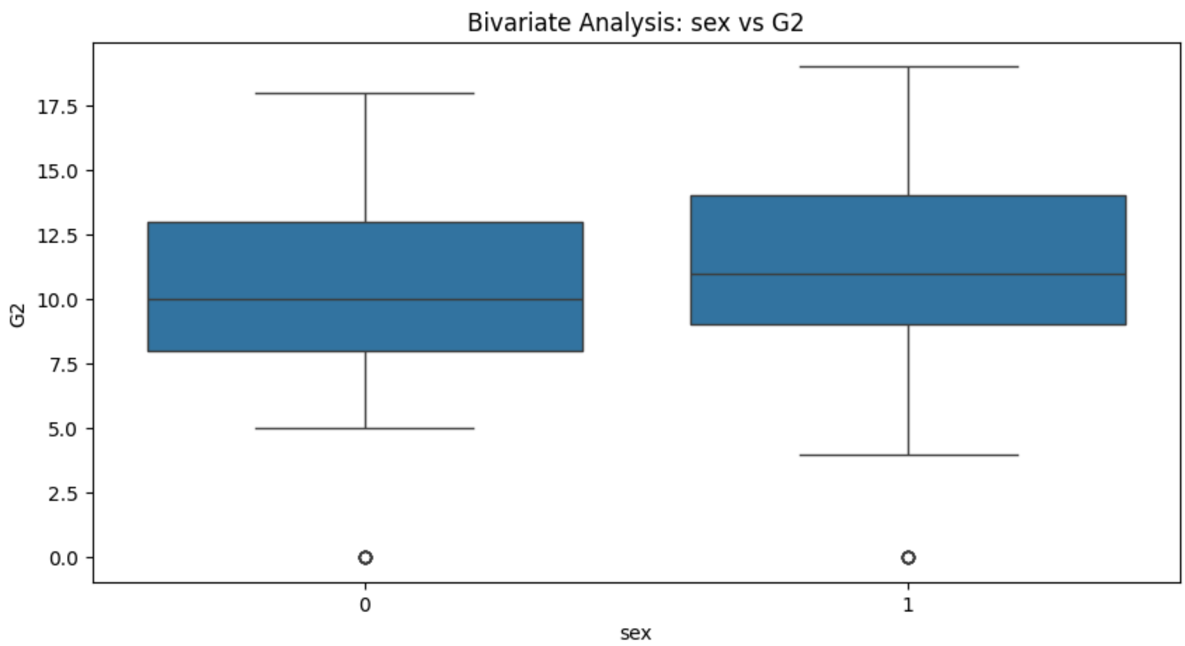

Bivariate Analysis: sex vs Dalc
Dalc
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0
1
sex

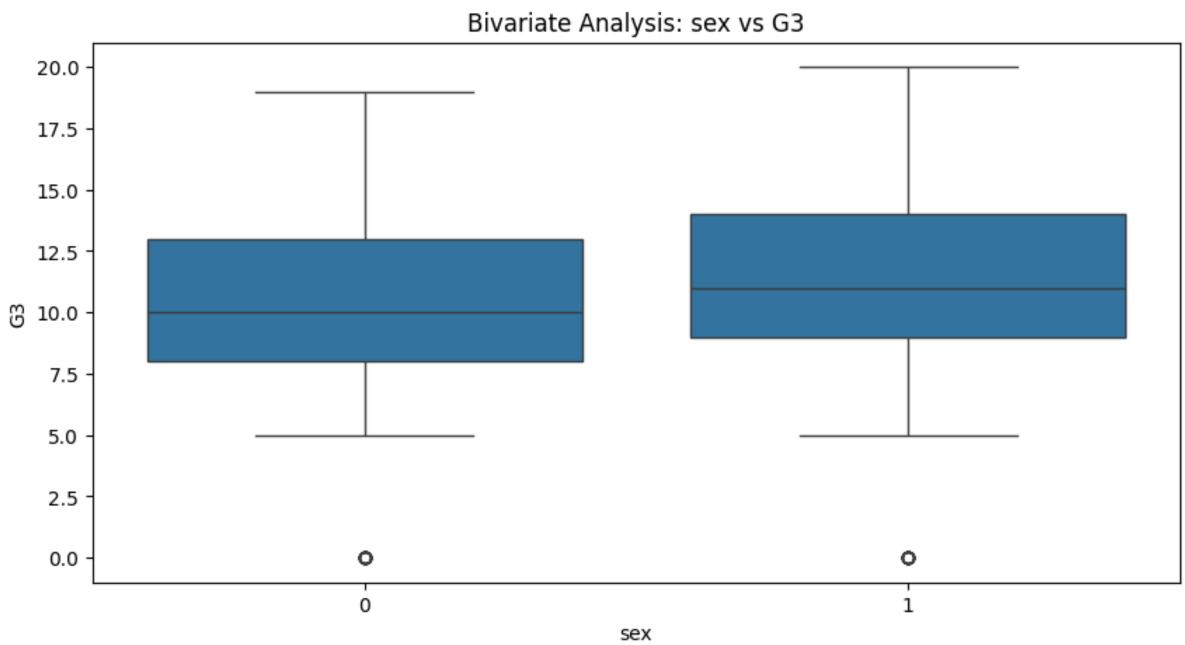

Bivariate Analysis: sex vs Walc
Walc
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0
1
sex

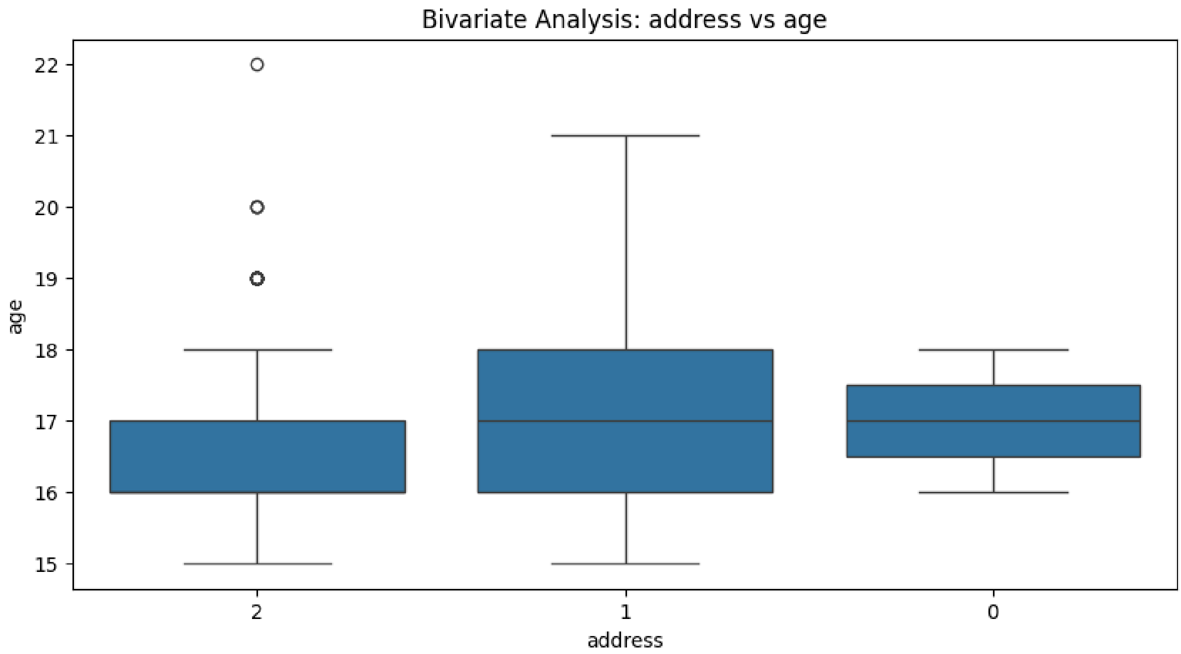

Bivariate Analysis: sex vs health
health
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0
1
sex

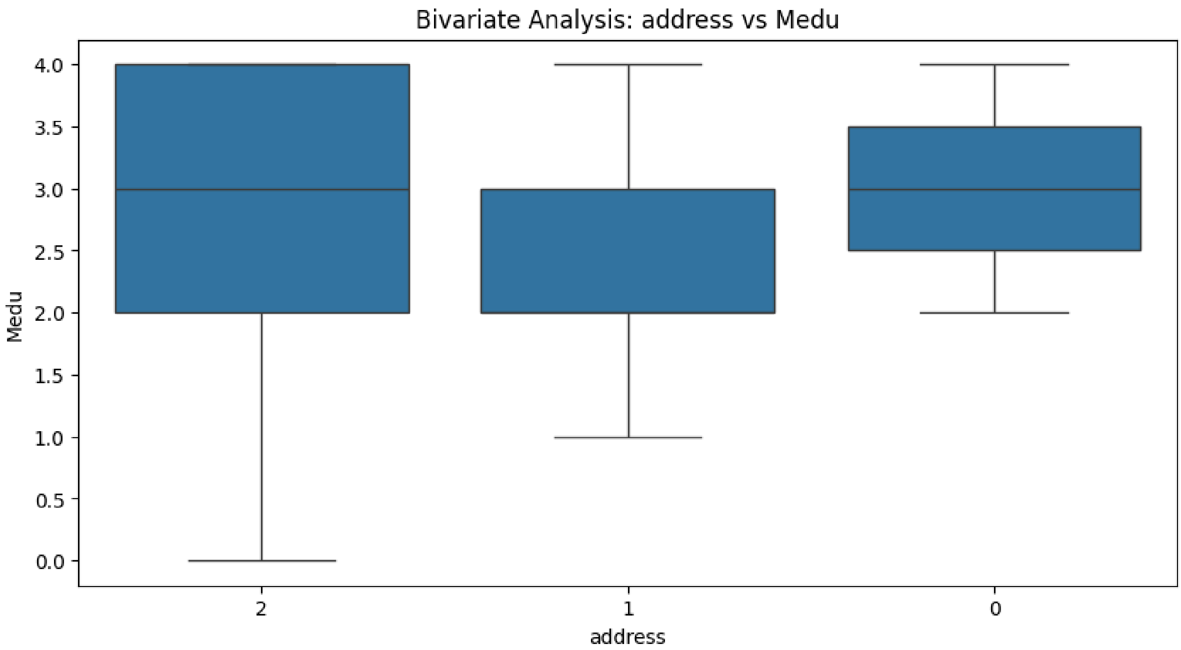

Bivariate Analysis: sex vs absences
absences
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0
1
sex

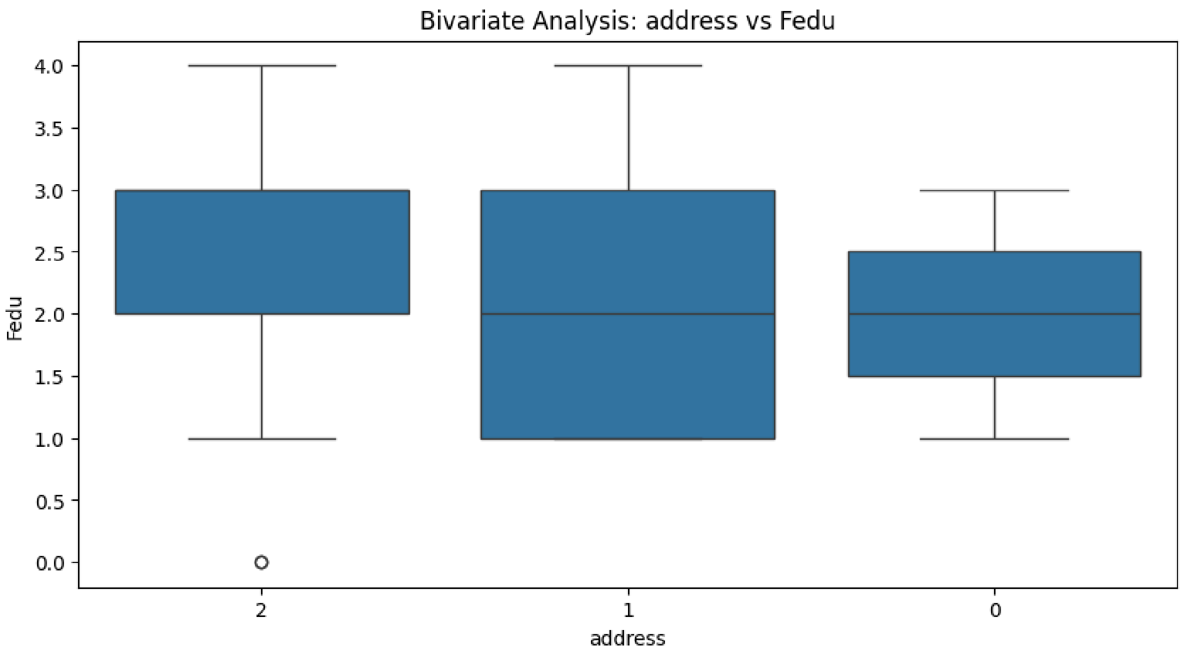

Bivariate Analysis: sex vs G1
G1
4
6
8
10
12
14
16
18
0
1
sex

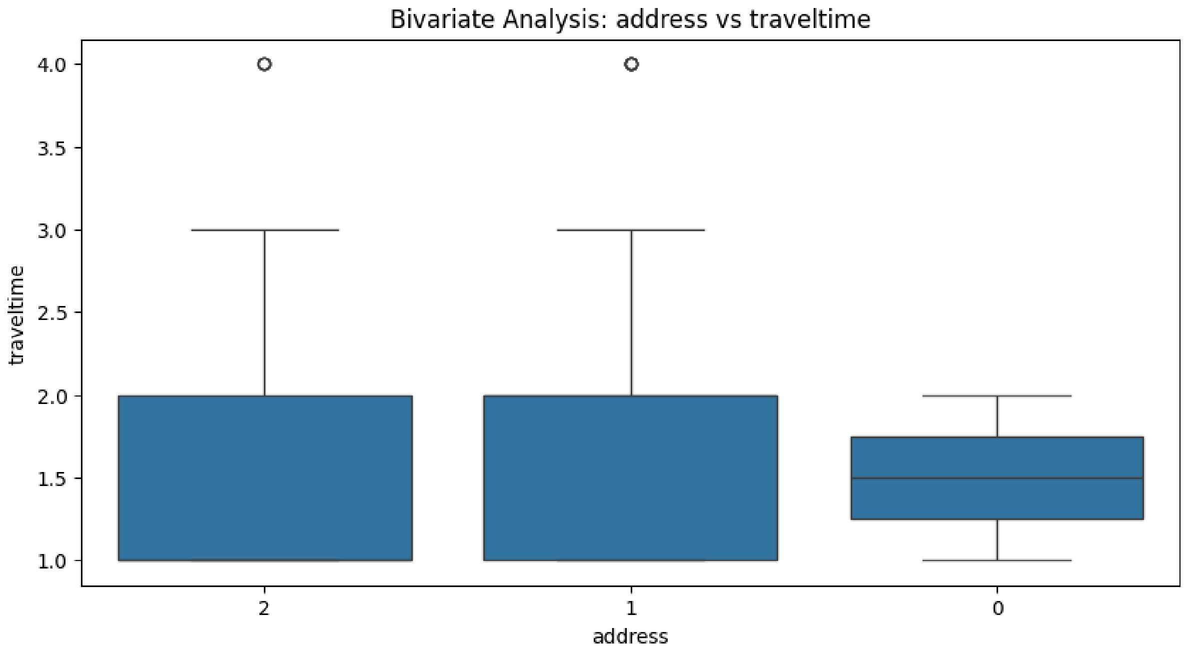

Bivariate Analysis: sex vs G2
G2
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
0
1
sex

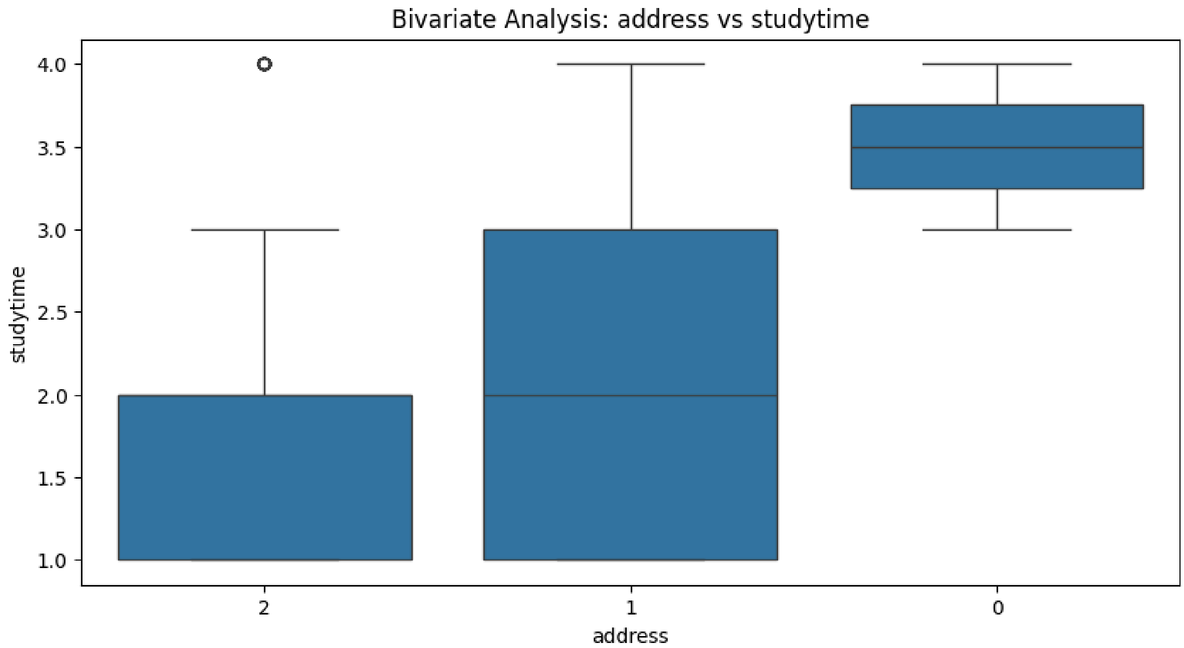

Bivariate Analysis: sex vs G3
G3
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
0
1
sex

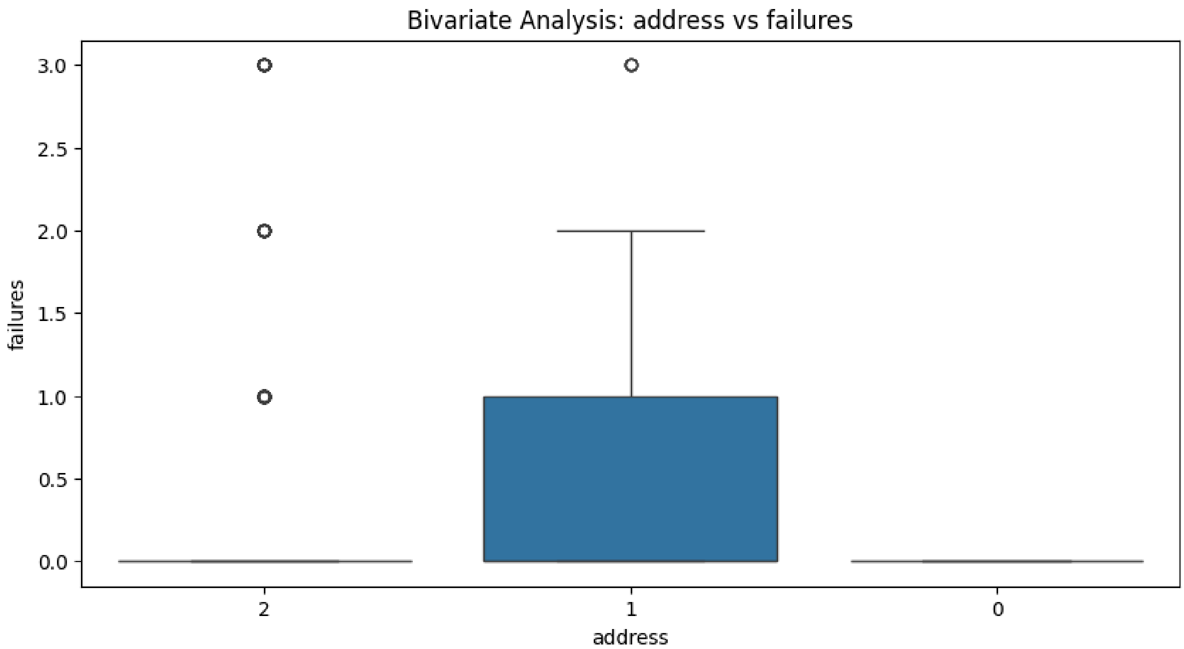

Bivariate Analysis: address vs age
age
22
21
20
19
18
17
16
15
2
1
0
address

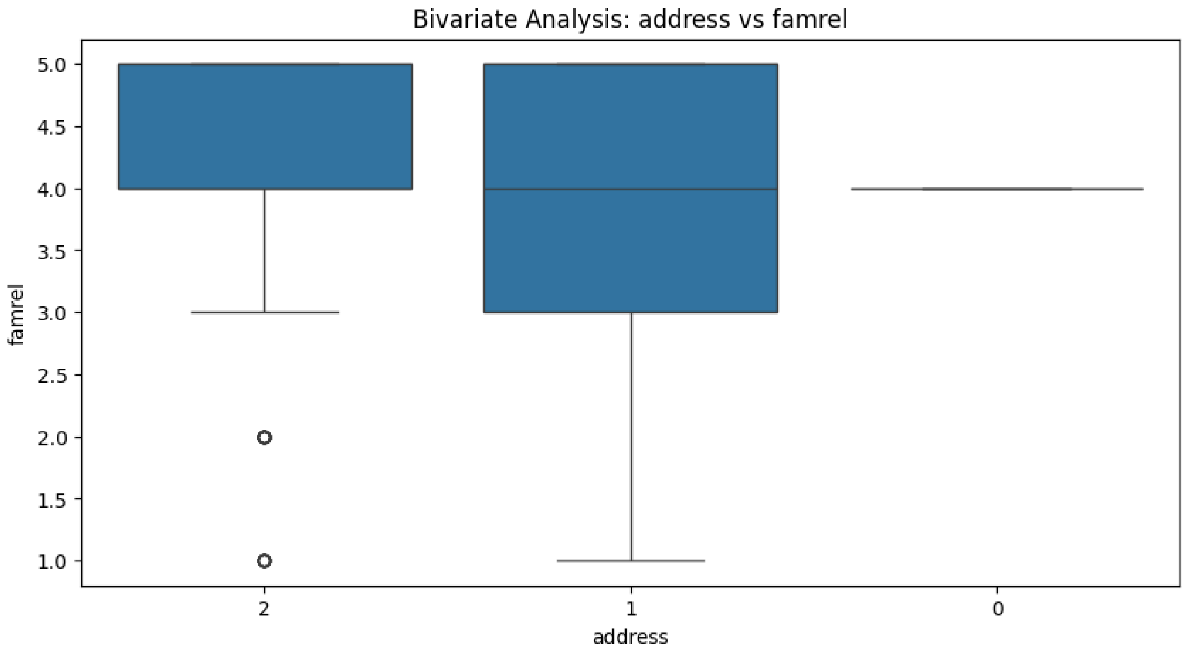

Bivariate Analysis: address vs Medu
Medu
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
2
1
0
address


Bivariate Analysis: address vs Fedu
Fedu
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
2
1
0
address

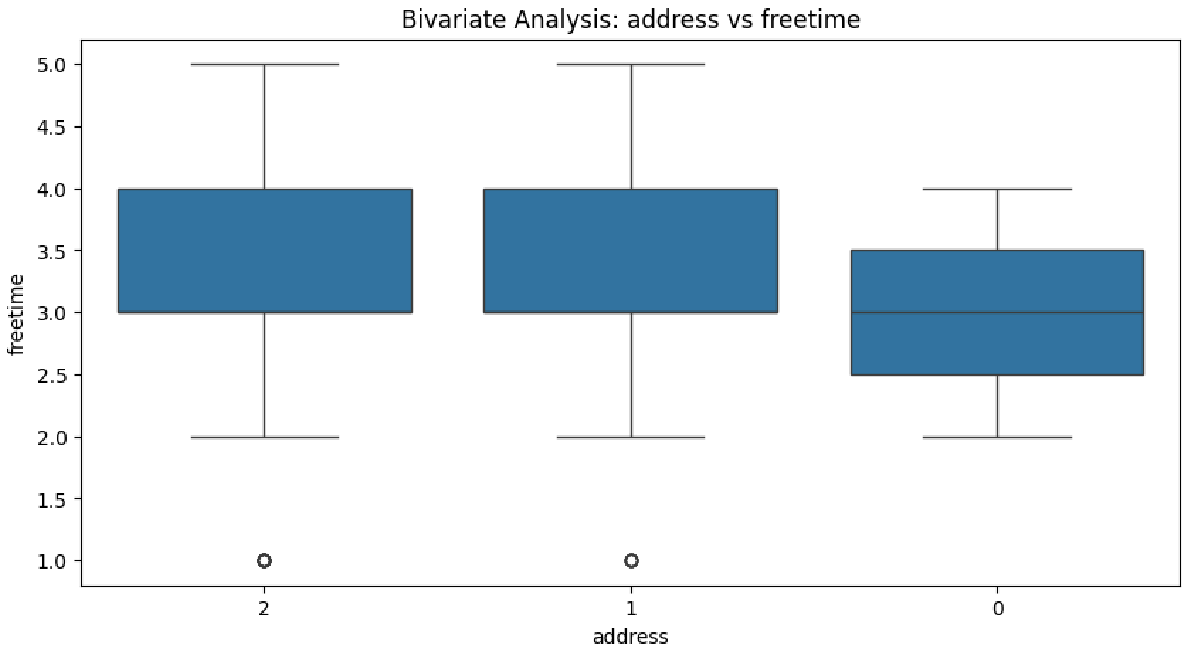

Bivariate Analysis: address vs traveltime
traveltime
4.0
3.5
3.0
2.5
2.0
1.5
1.0
2
1
0
address


Bivariate Analysis: address vs studytime
studytime
4.0
3.5
3.0
2.5
2.0
1.5
1.0
2
1
0
address

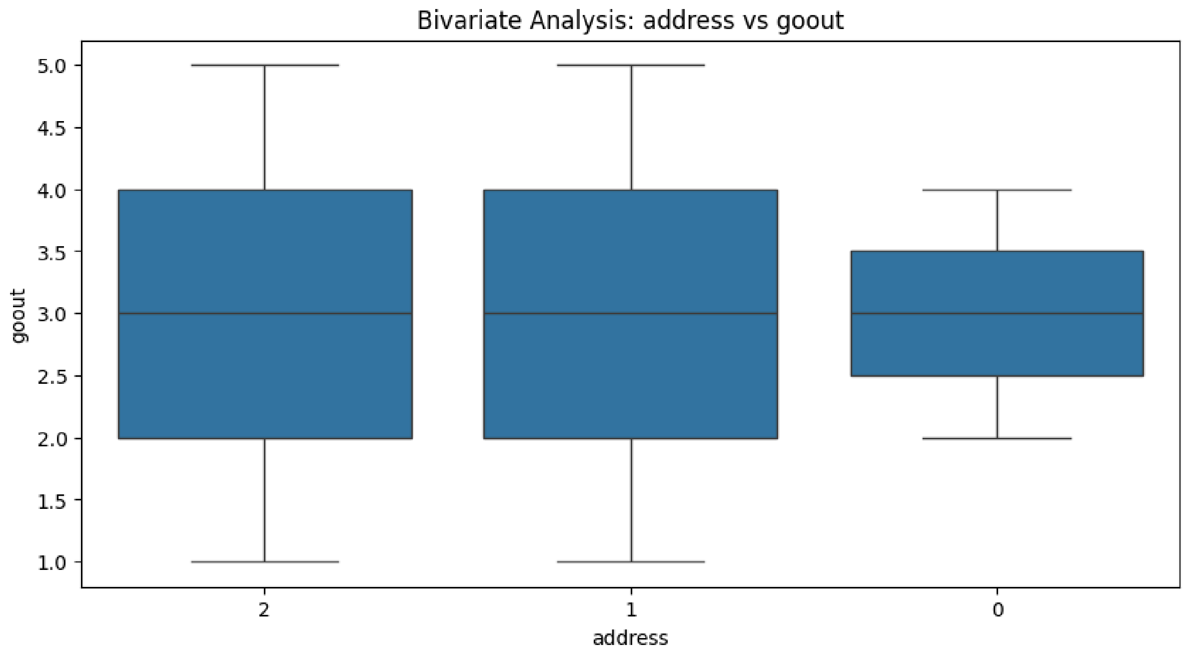

Bivariate Analysis: address vs failures
failures
3.0
2.5
2.0
1.5
1.0
0.5
0.0
2
1
0
address



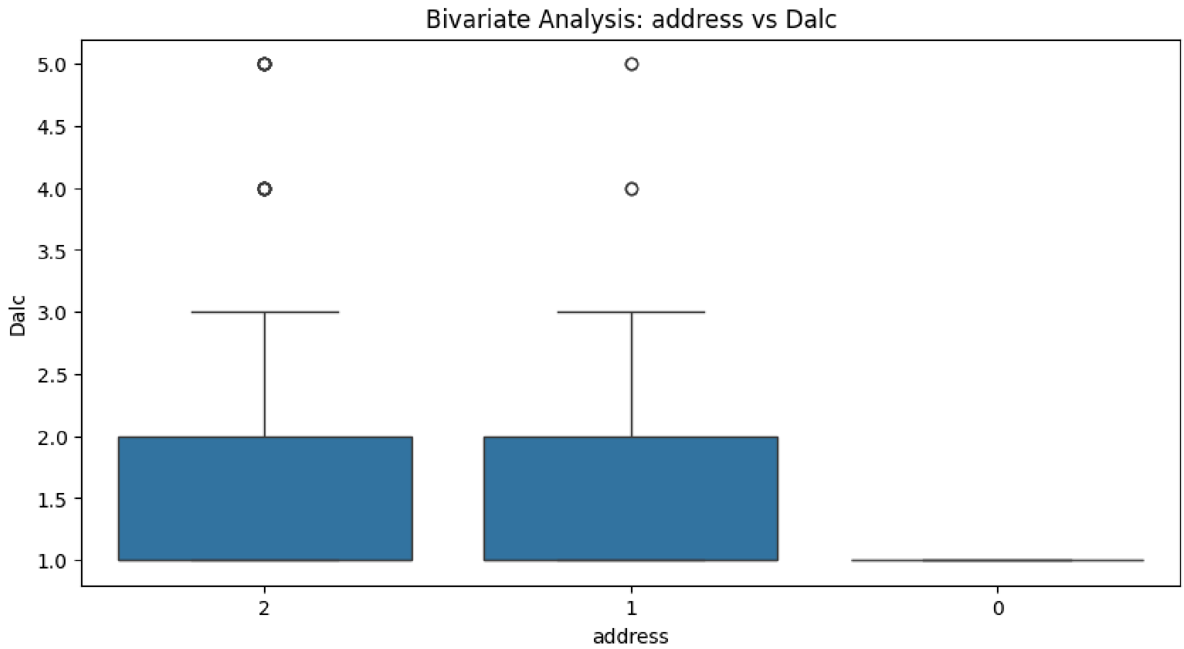
Bivariate Analysis: address vs famrel
famrel
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
2
1
0
address

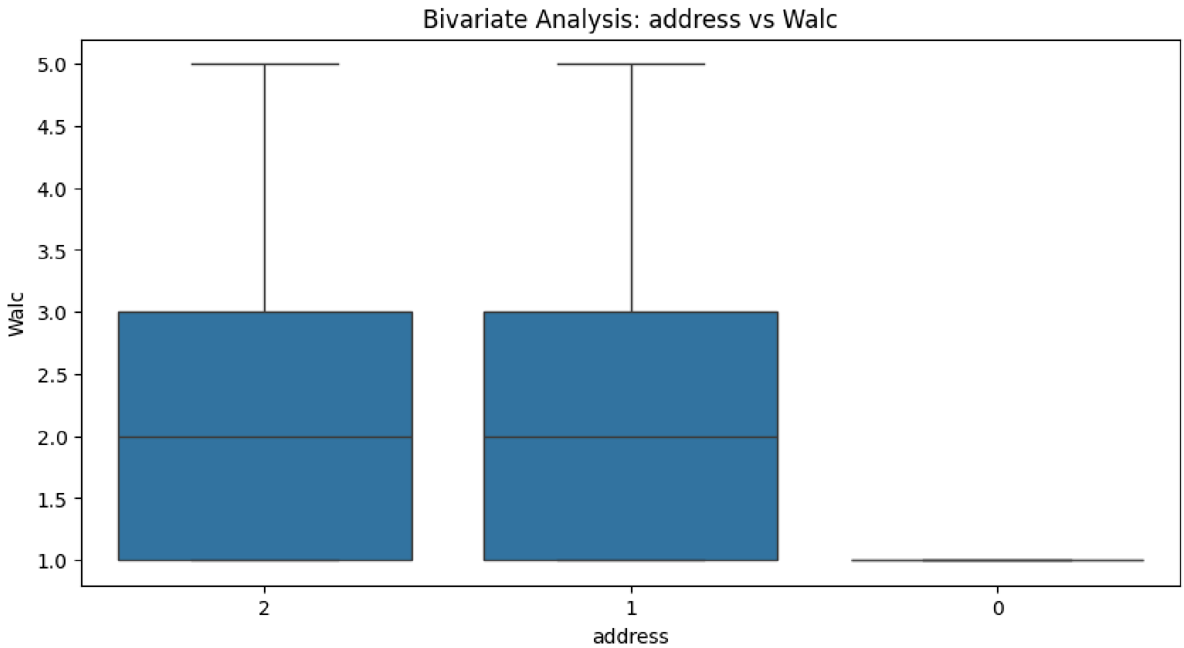


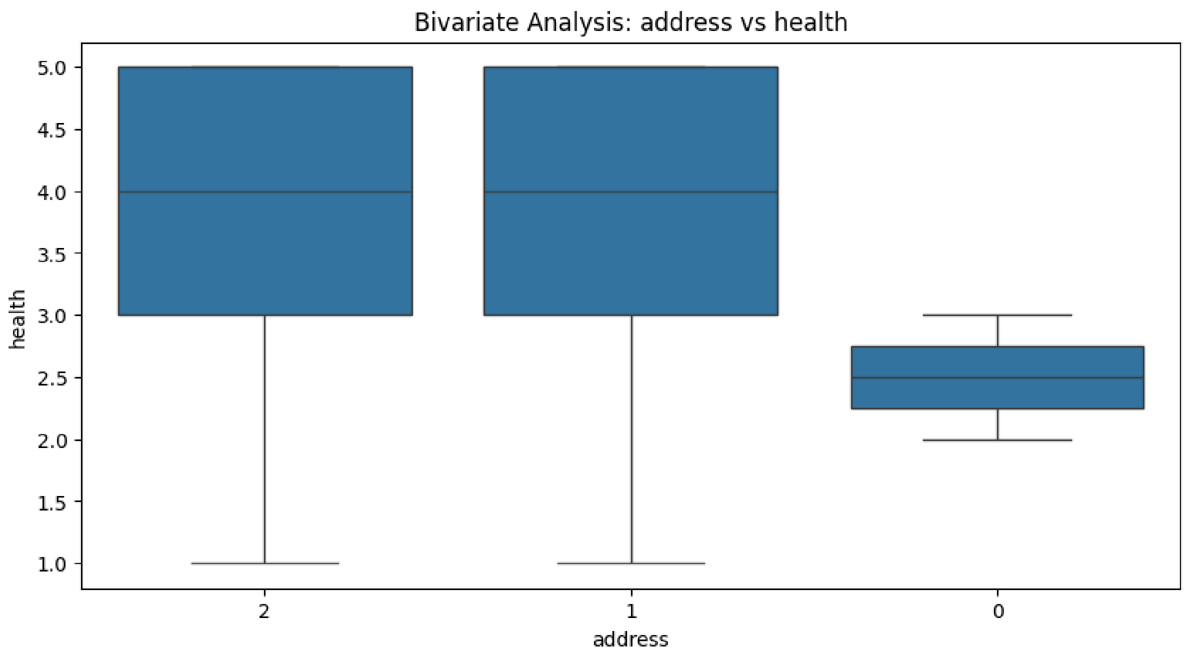
Bivariate Analysis: address vs freetime
freetime
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
2
1
0
address

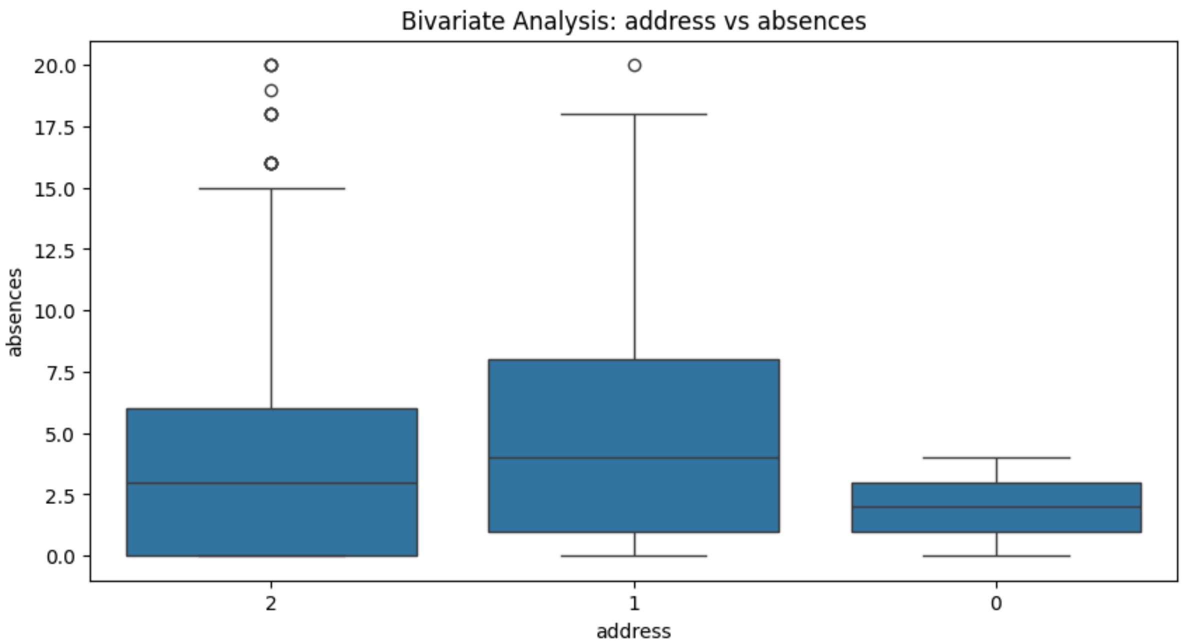


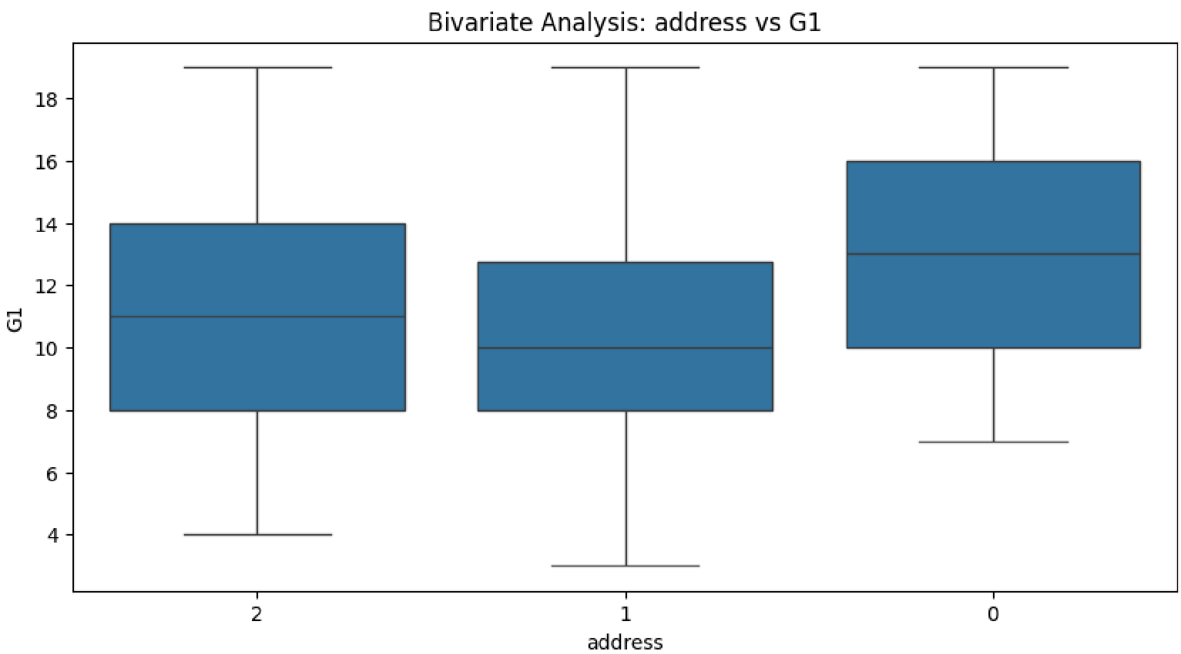
Bivariate Analysis: address vs goout
goout
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
2
1
0
address

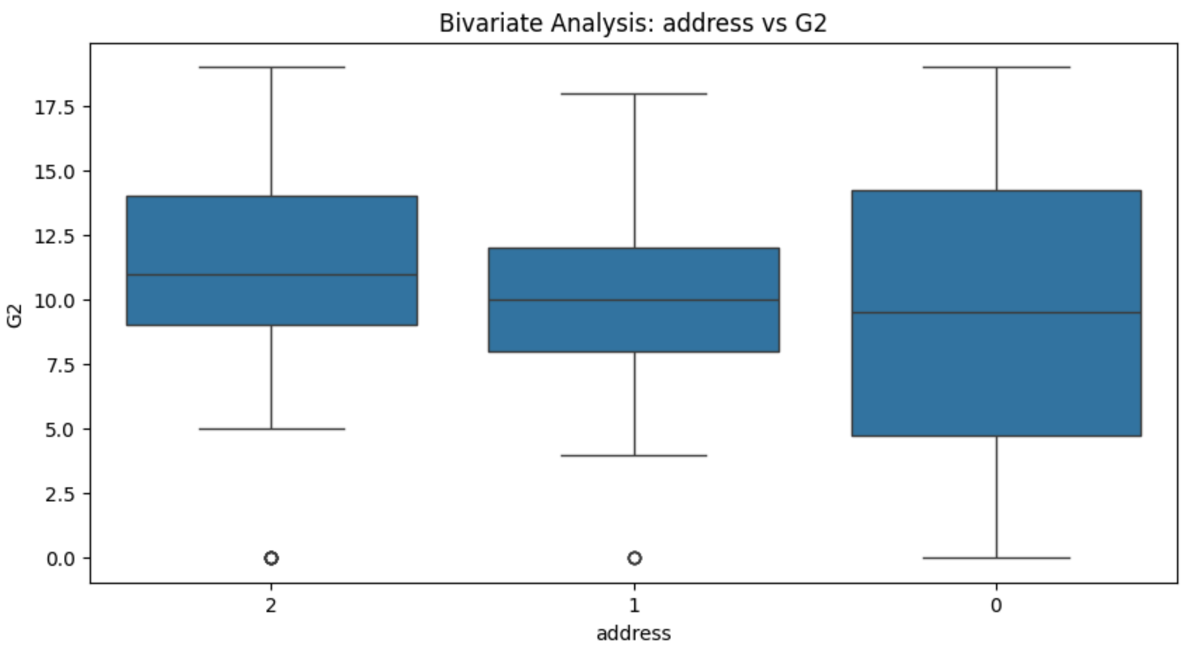

Bivariate Analysis: address vs Dalc
Dalc
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
2
1
0
address

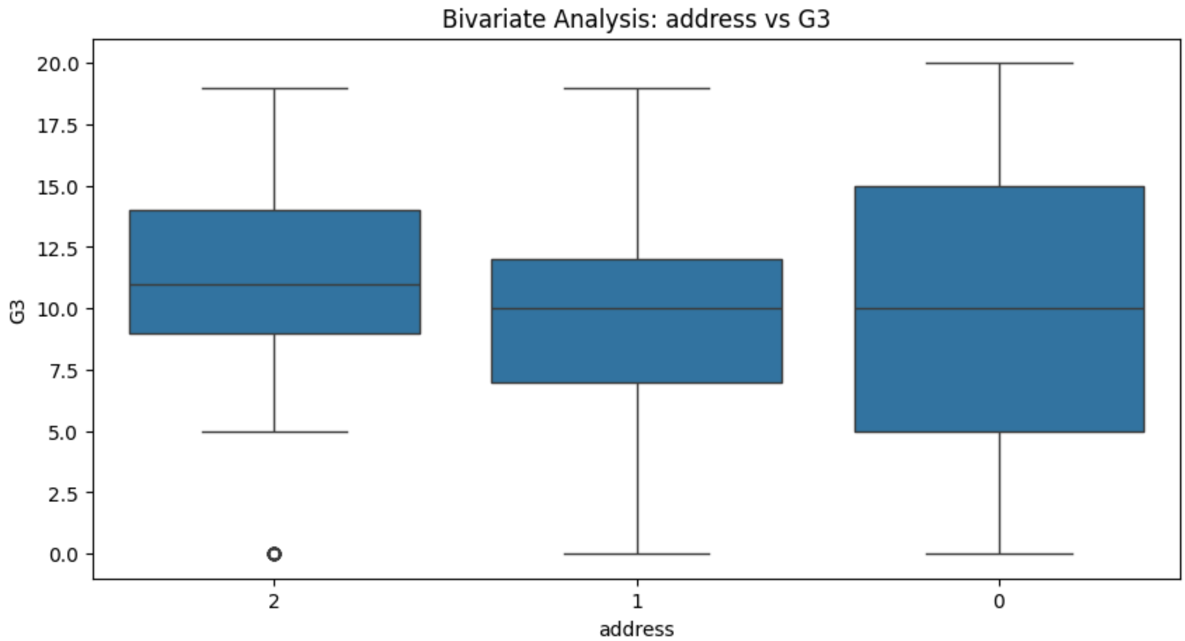

Bivariate Analysis: address vs Walc
Walc
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
2
1
0
address

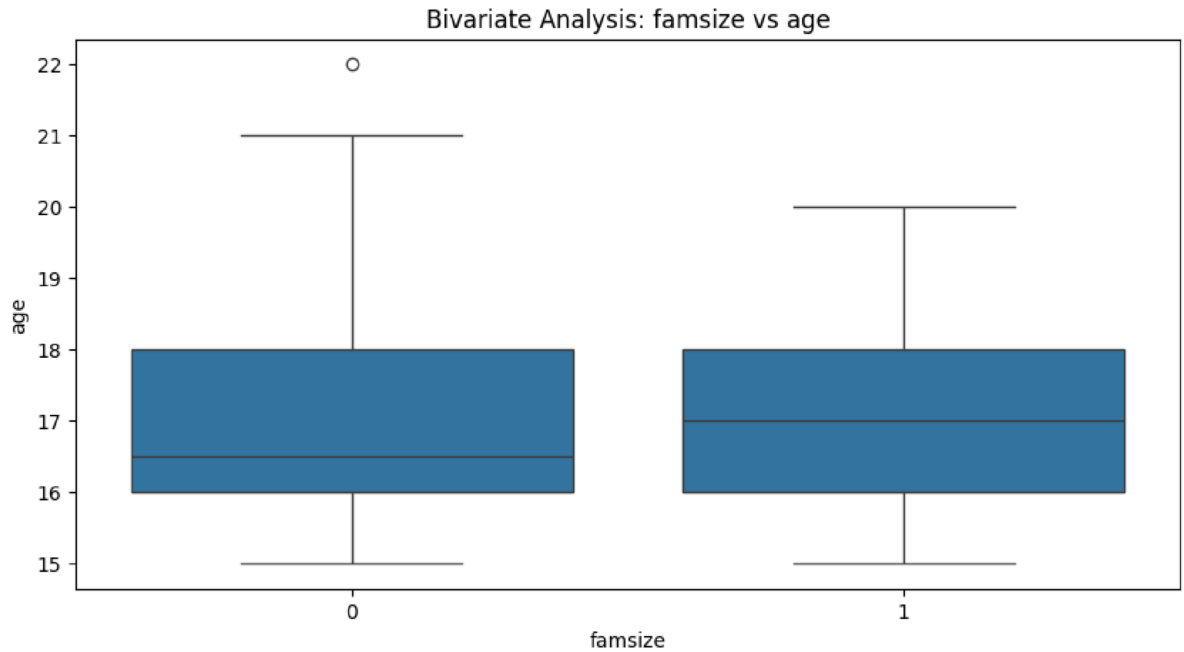

Bivariate Analysis: address vs health
health
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
2
1
0
address

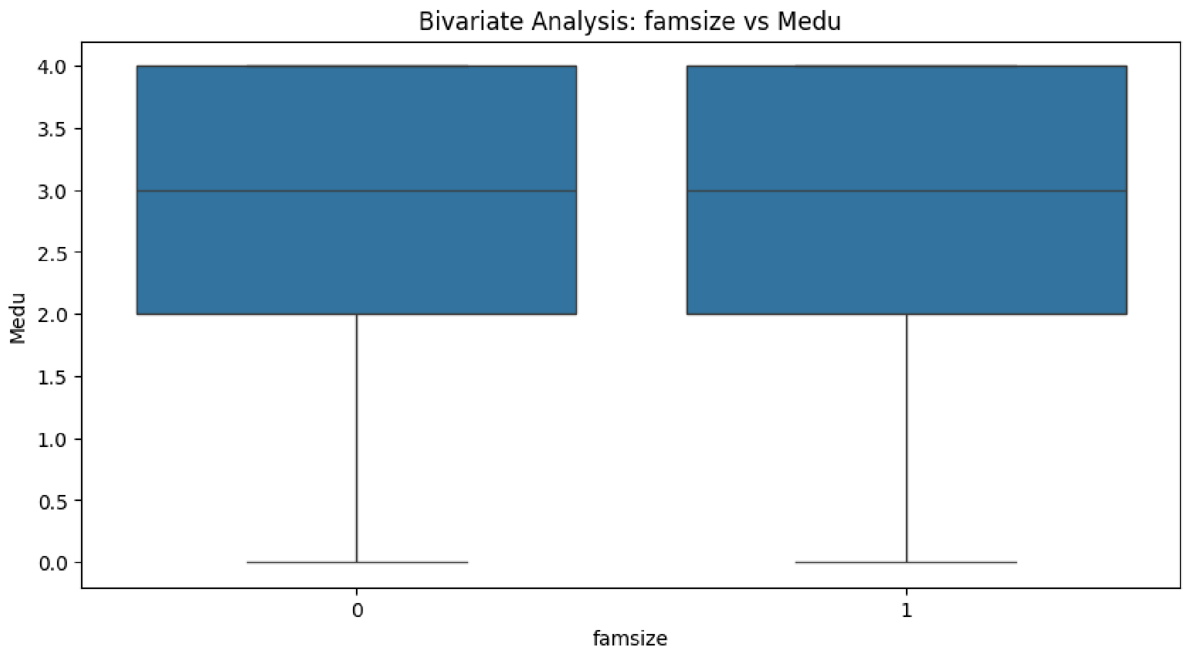

Bivariate Analysis: address vs absences
absences
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
2
1
0
address

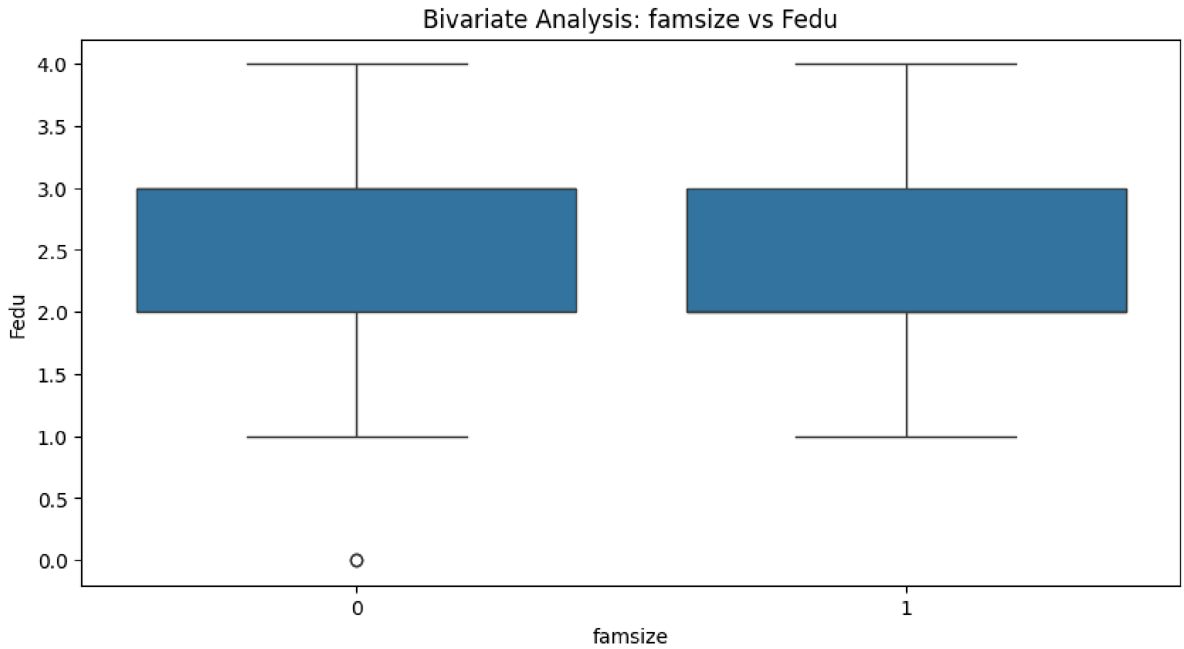

Bivariate Analysis: address vs G1
G1
18
16
14
12
10
8
6
4
2
1
0
address


Bivariate Analysis: address vs G2
G2
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
2
1
0
address

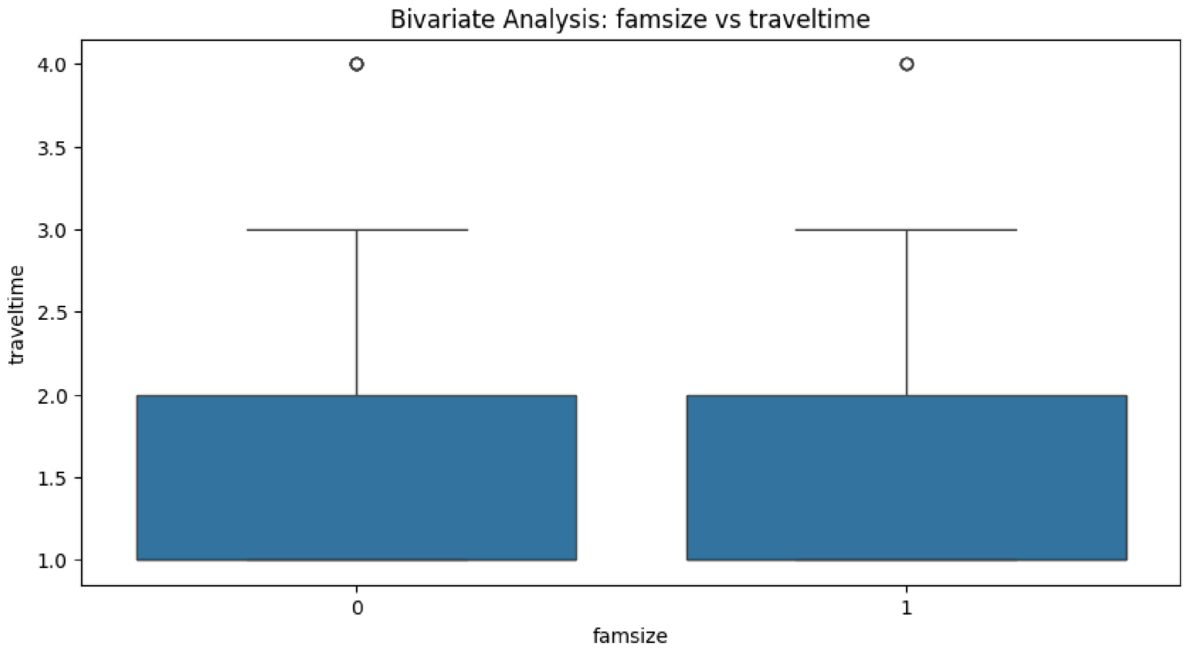

Bivariate Analysis: address vs G3
G3
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
2
1
0
address


Bivariate Analysis: famsize vs age
age
22
21
20
19
18
17
16
15
0
1
famsize

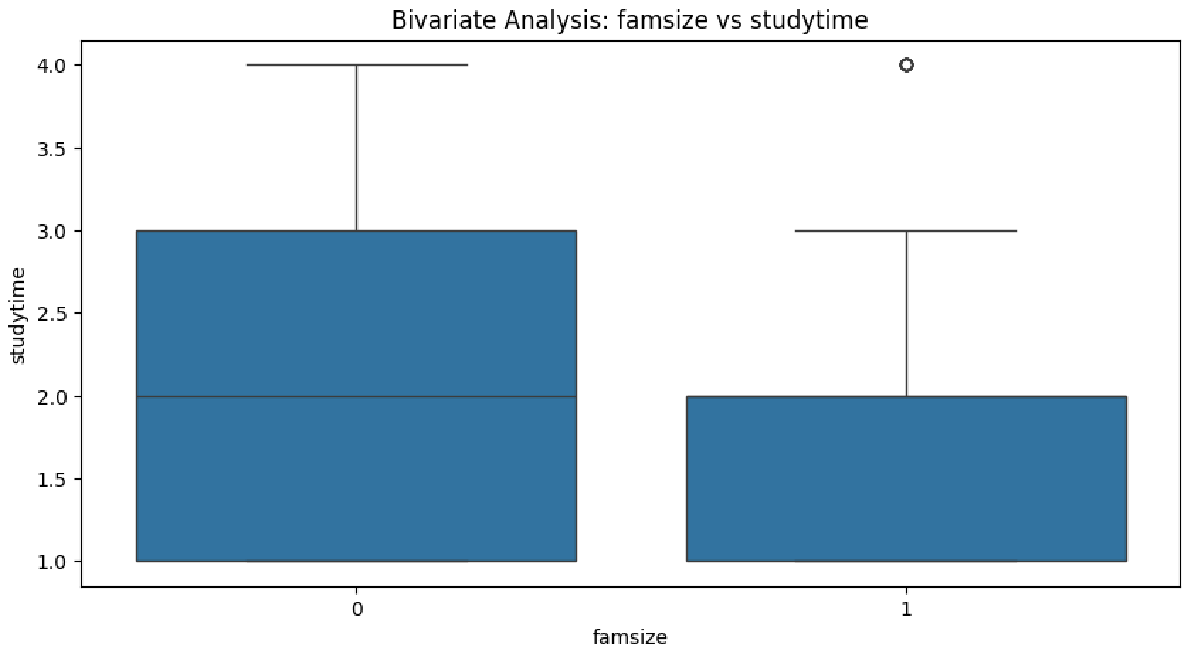

Bivariate Analysis: famsize vs Medu
Medu
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
1
famsize



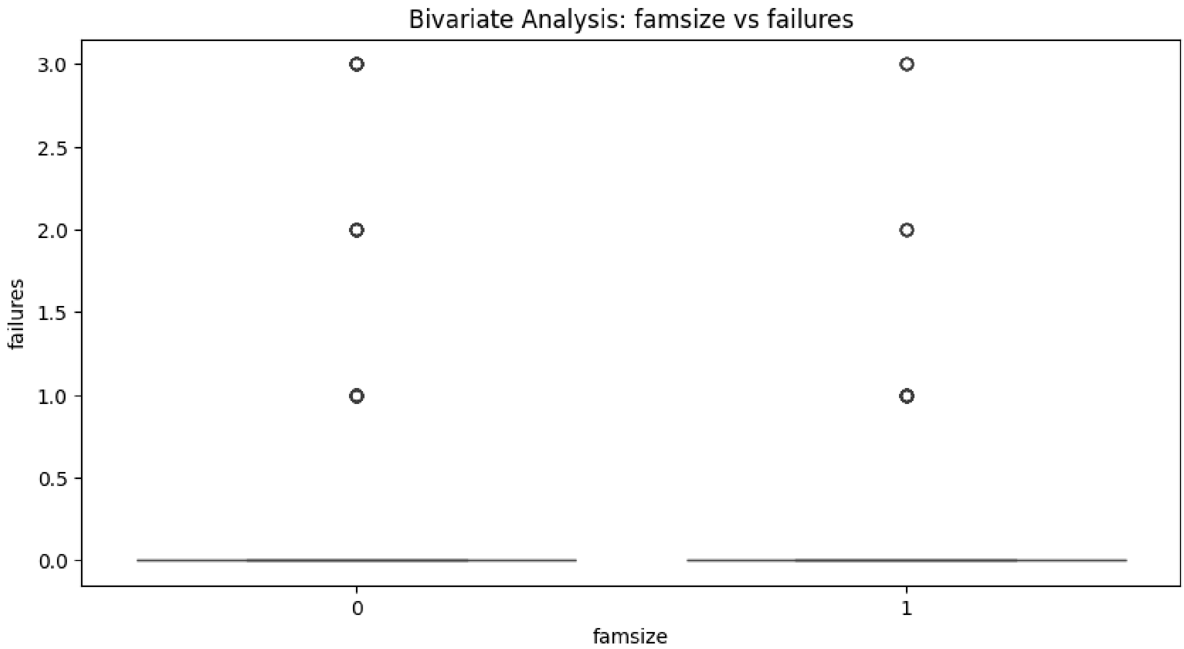
Bivariate Analysis: famsize vs Fedu
Fedu
famsize

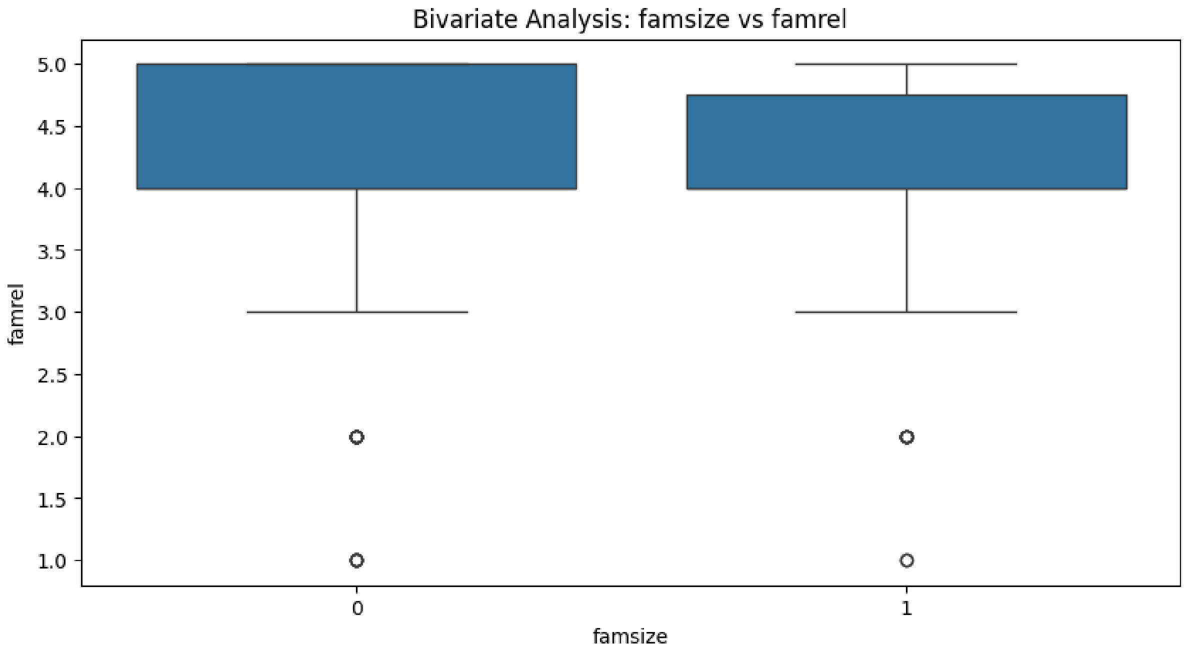


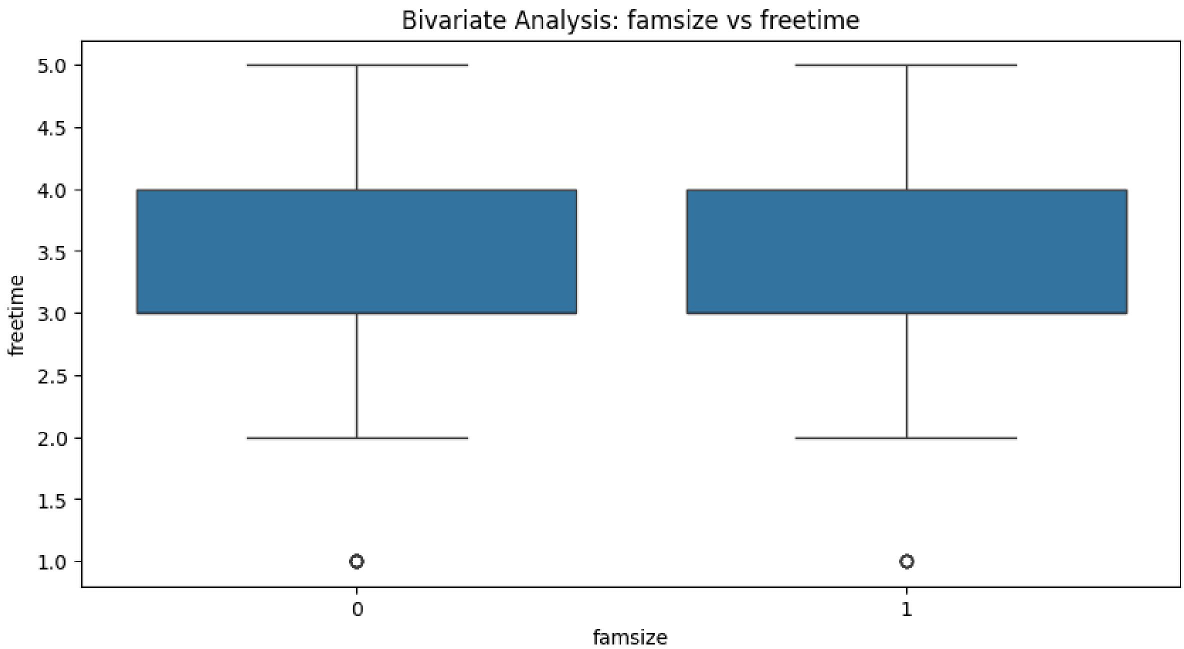
Bivariate Analysis: famsize vs traveltime
traveltime
famsize

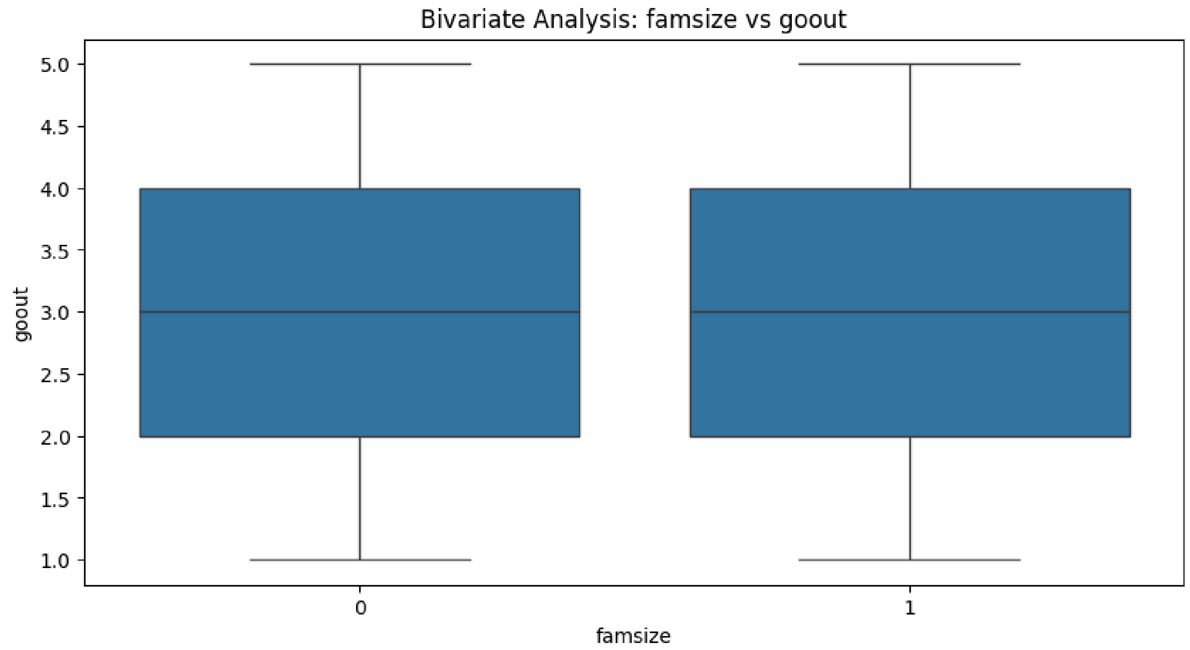


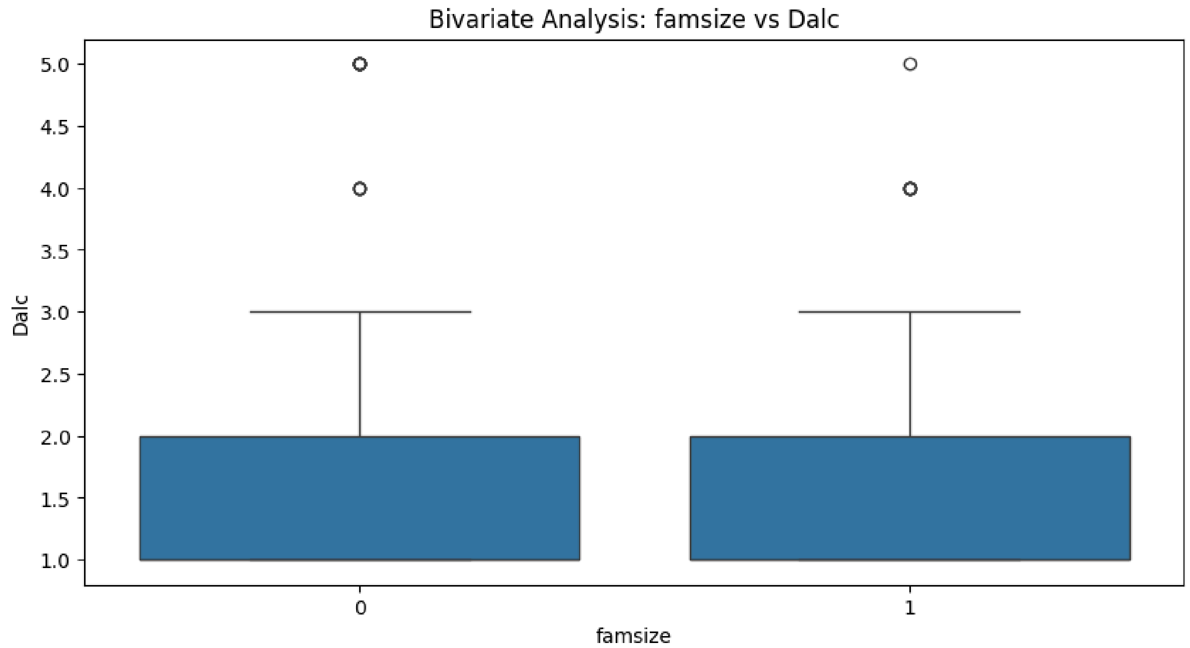
Bivariate Analysis: famsize vs studytime
studytime
famsize

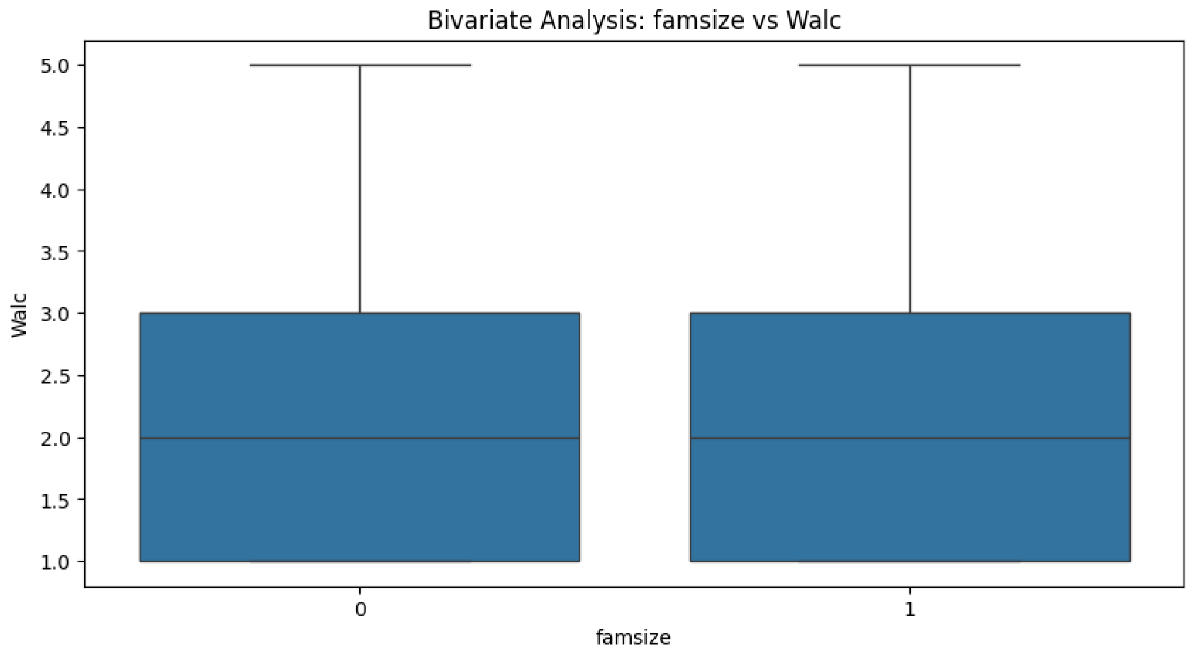

Bivariate Analysis: famsize vs failures
failures
famsize
0
1
0.0
0.5
1.0
1.5
2.0
2.5
3.0

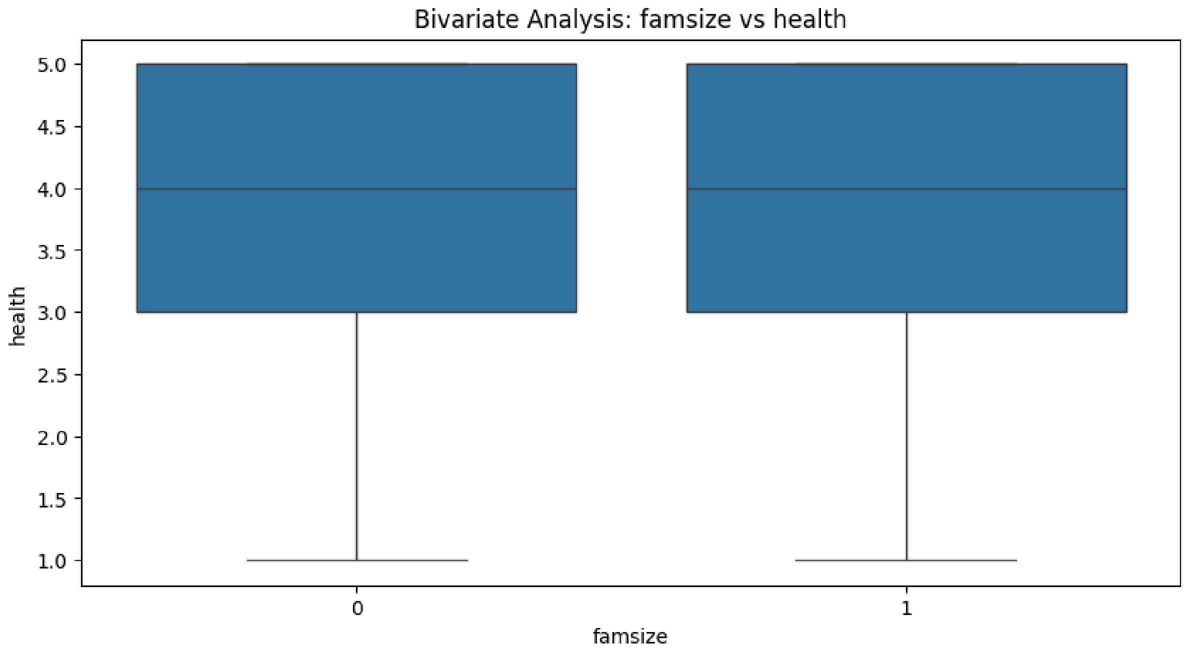

Bivariate Analysis: famsize vs famrel
famrel
famsize
0
1
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0

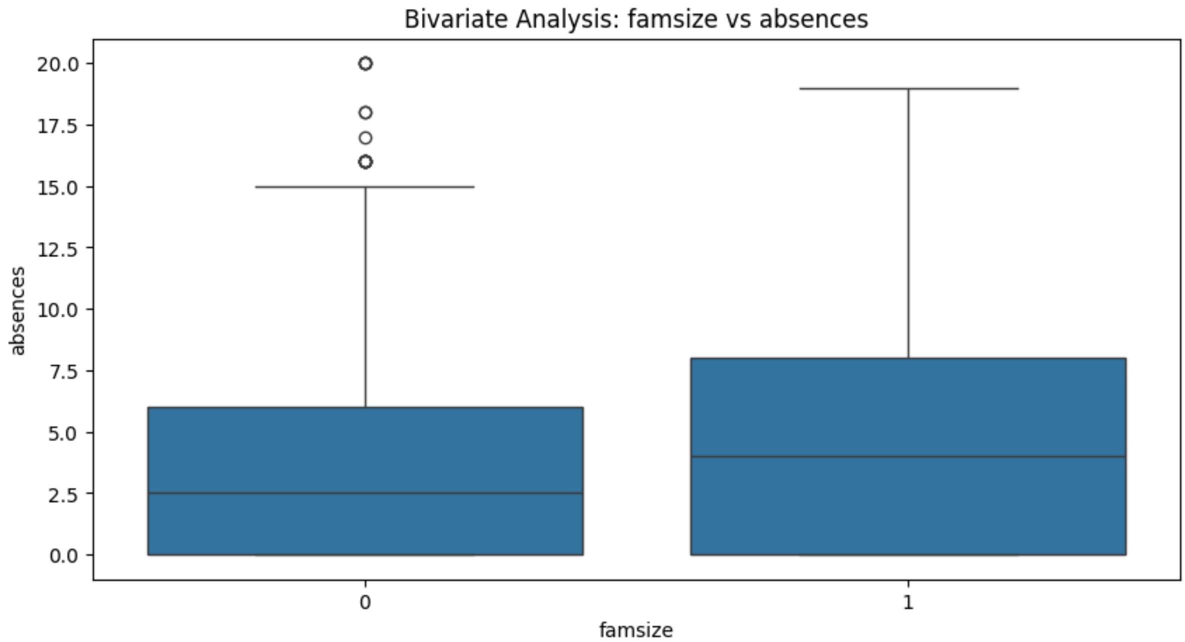

Bivariate Analysis: famsize vs freetime
freetime
famsize
0
1
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0

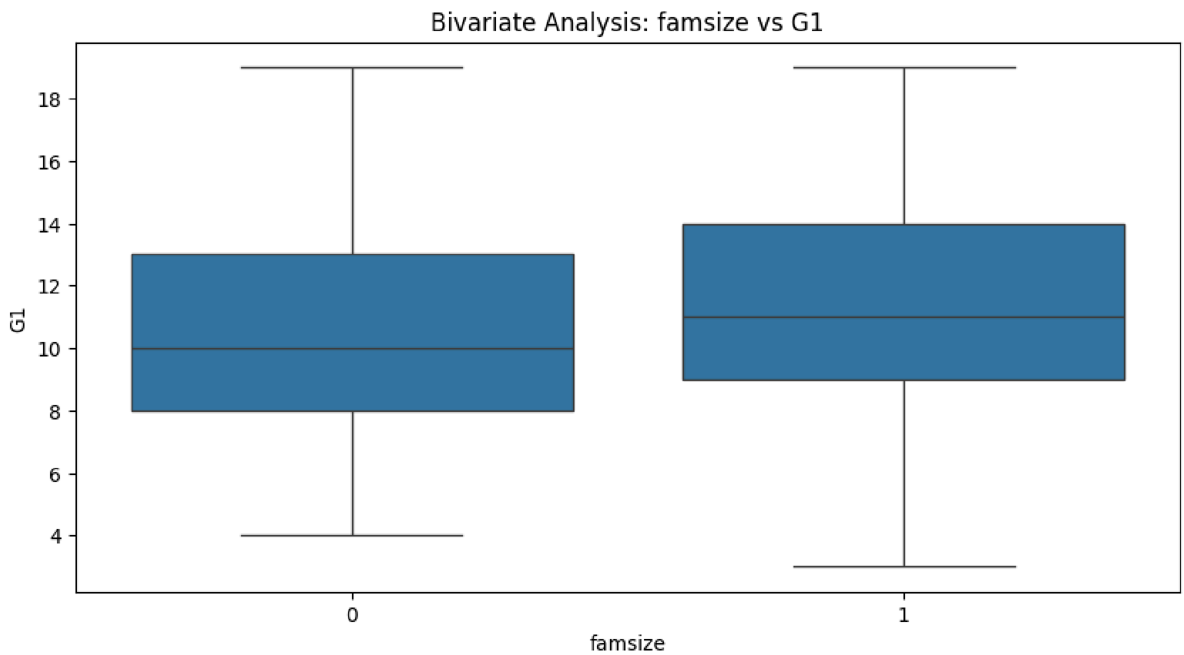

Bivariate Analysis: famsize vs goout
goout
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0
1
famsize

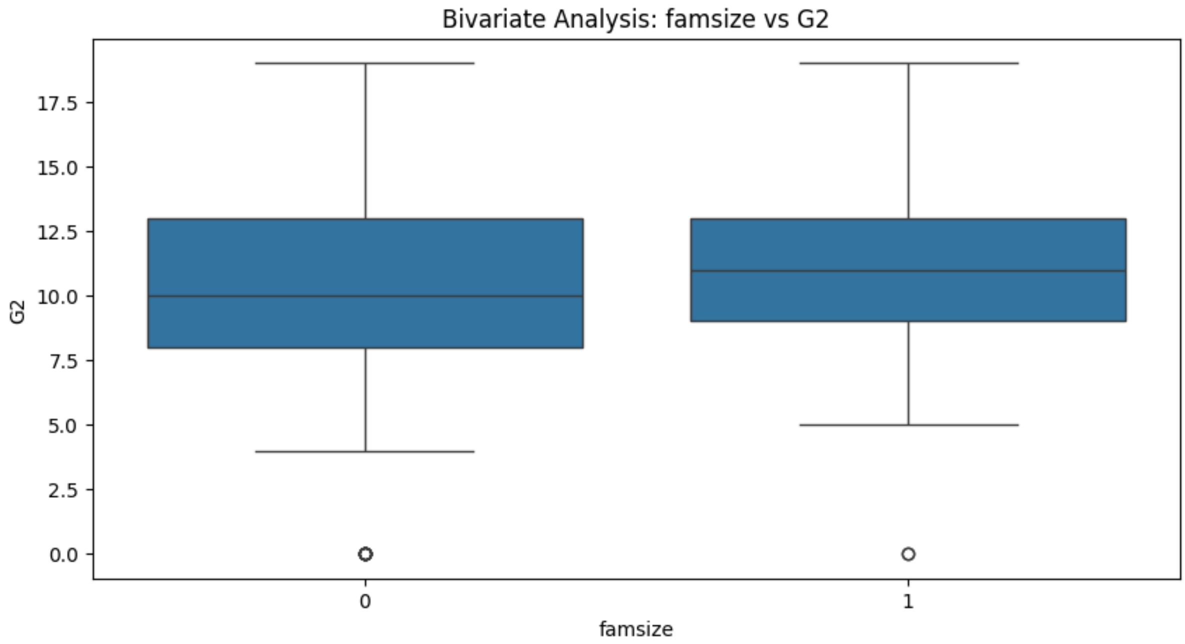

Bivariate Analysis: famsize vs Dalc
Dalc
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0
1
famsize


Bivariate Analysis: famsize vs Walc
Walc
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0
1
famsize

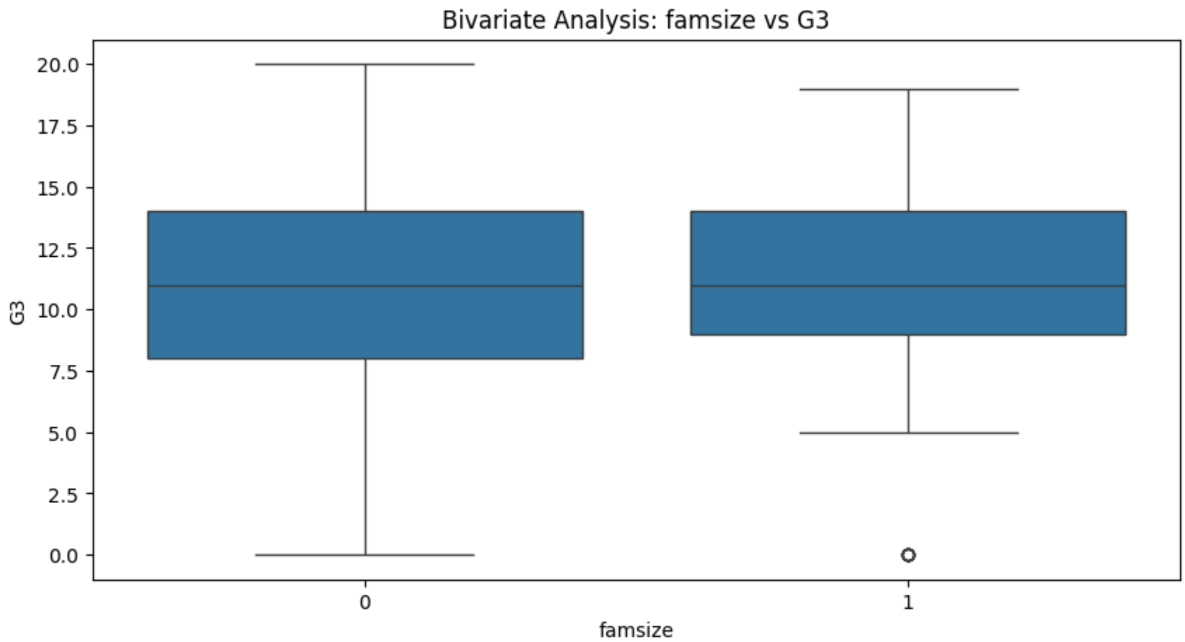

Bivariate Analysis: famsize vs health
health
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0
1
famsize


Bivariate Analysis: famsize vs absences
absences
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0
1
famsize


Bivariate Analysis: famsize vs G1
G1
18
16
14
12
10
8
6
4
0
1
famsize



Bivariate Analysis: famsize vs G2
G2
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0
1
famsize



Bivariate Analysis: famsize vs G3
G3
20.0
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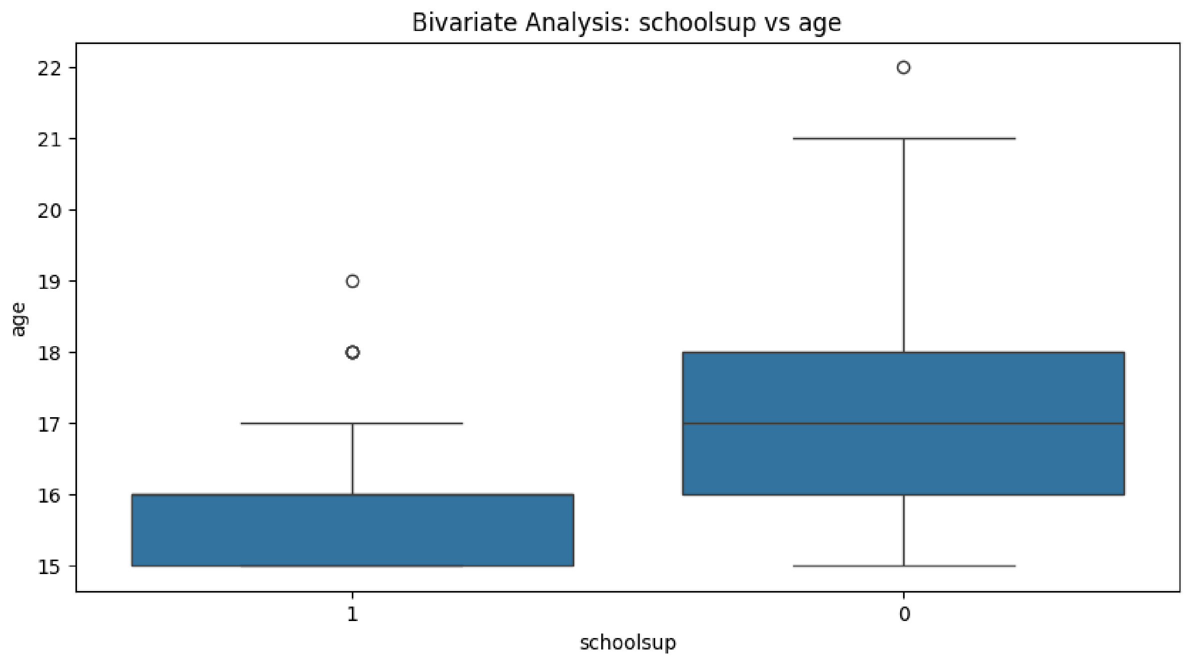
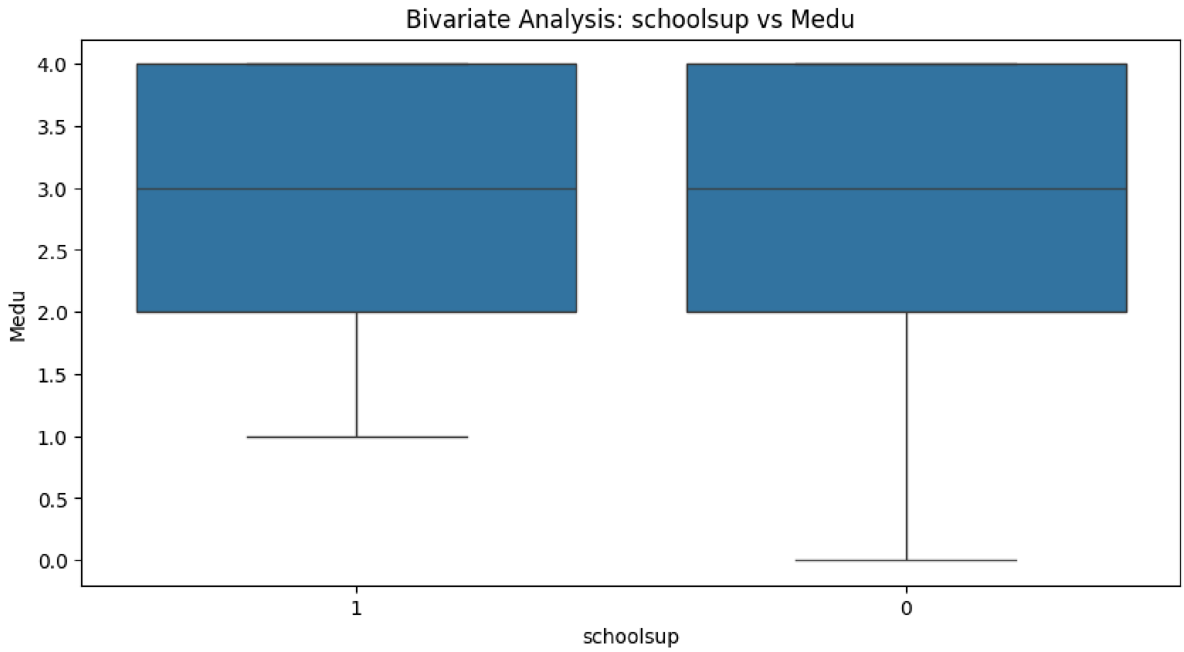
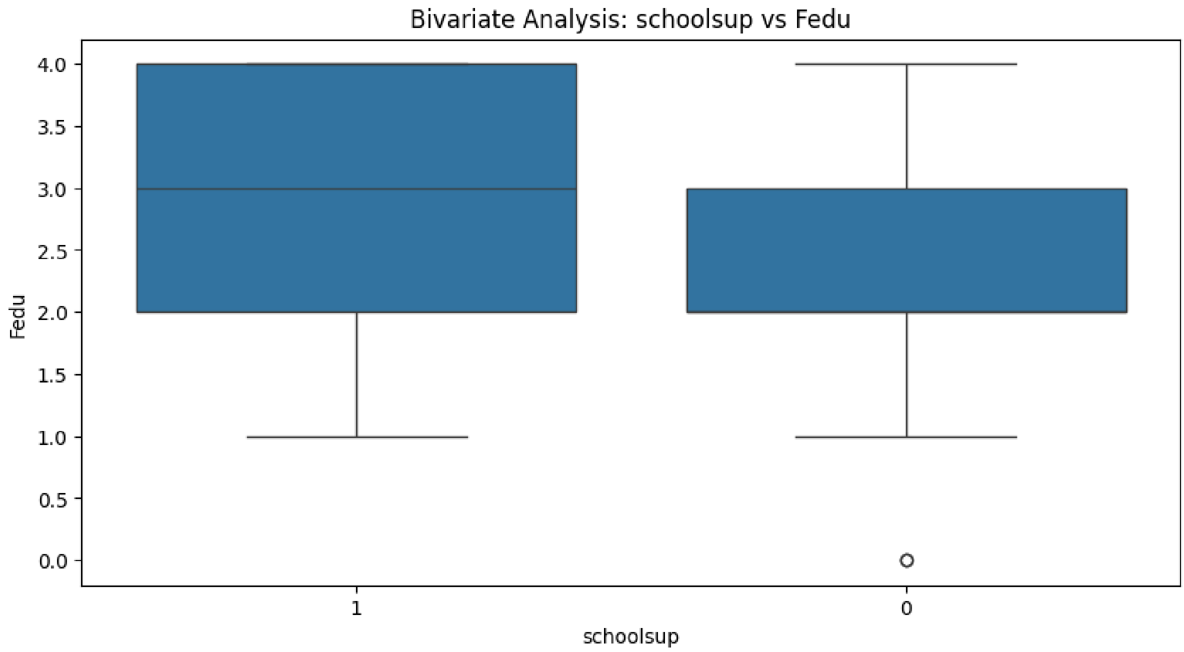
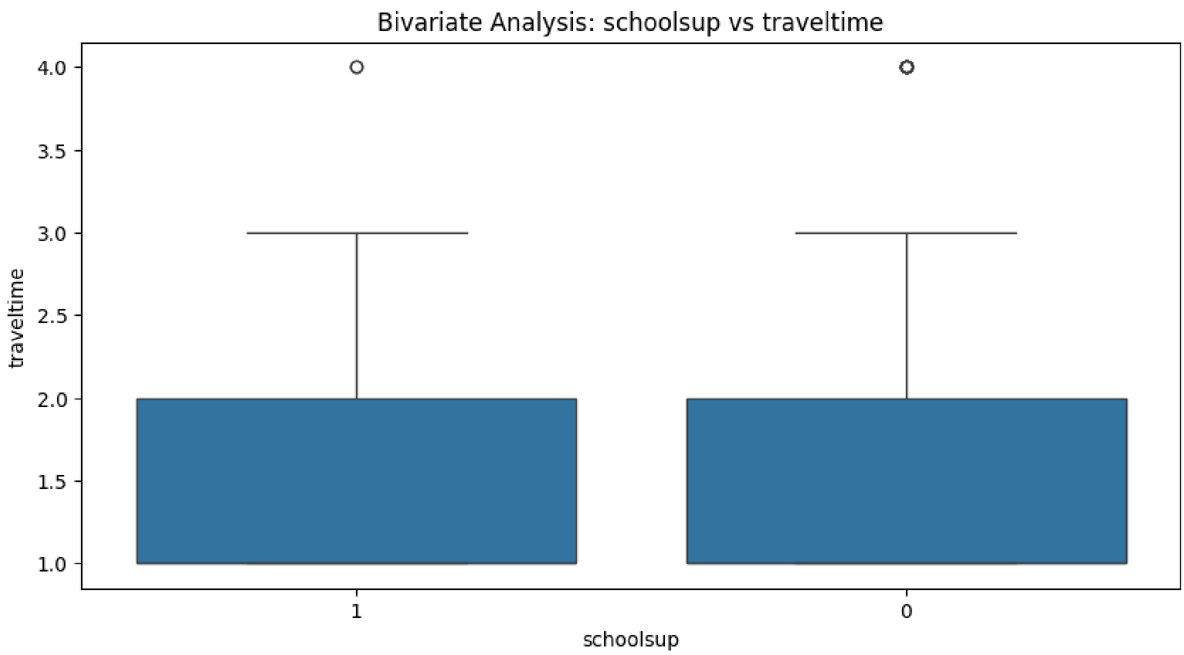
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0
1
famsize

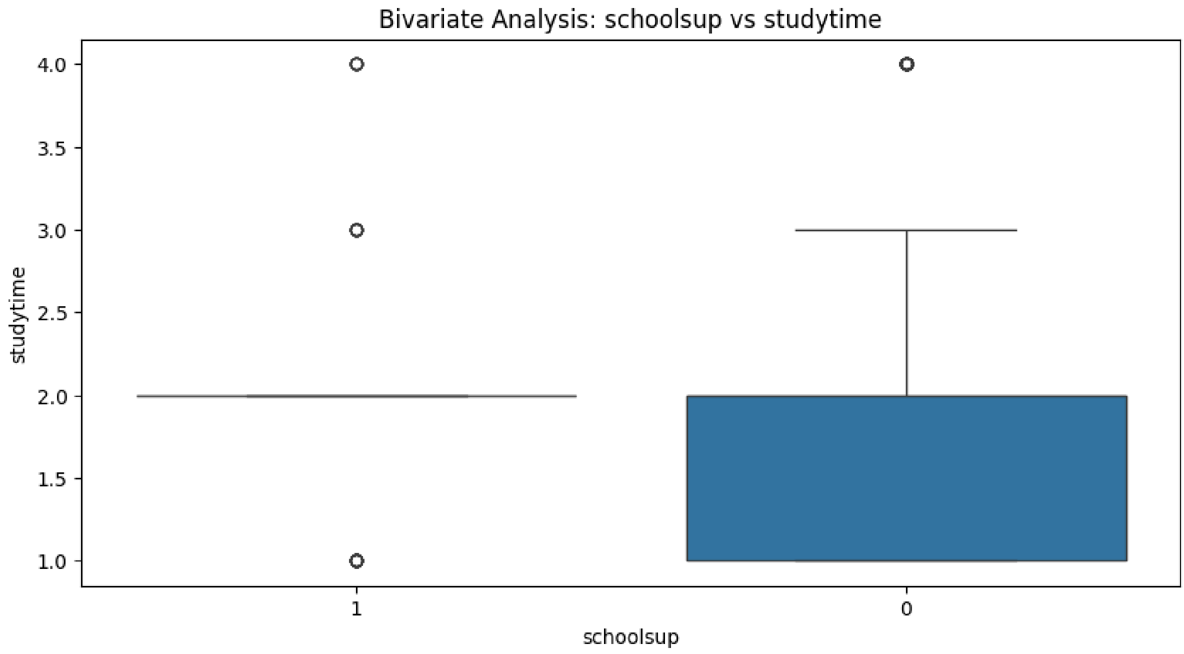


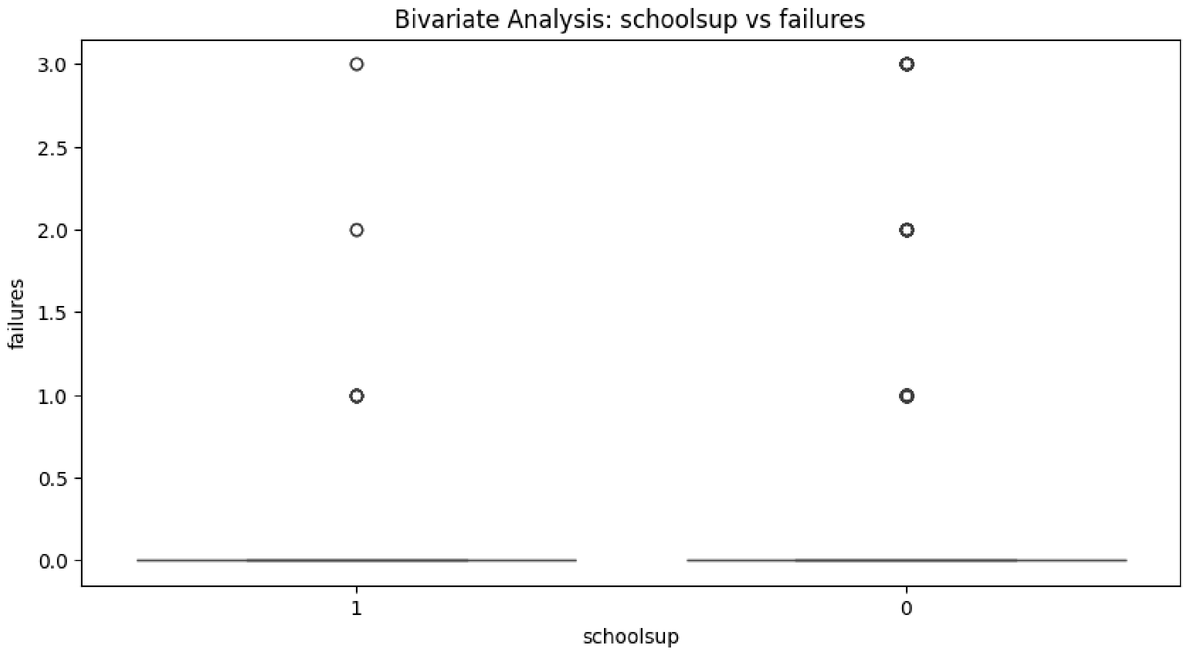
Bivariate Analysis: schoolsup vs age
age
22
21
20
19
18
17
16
15
1
0
schoolsup

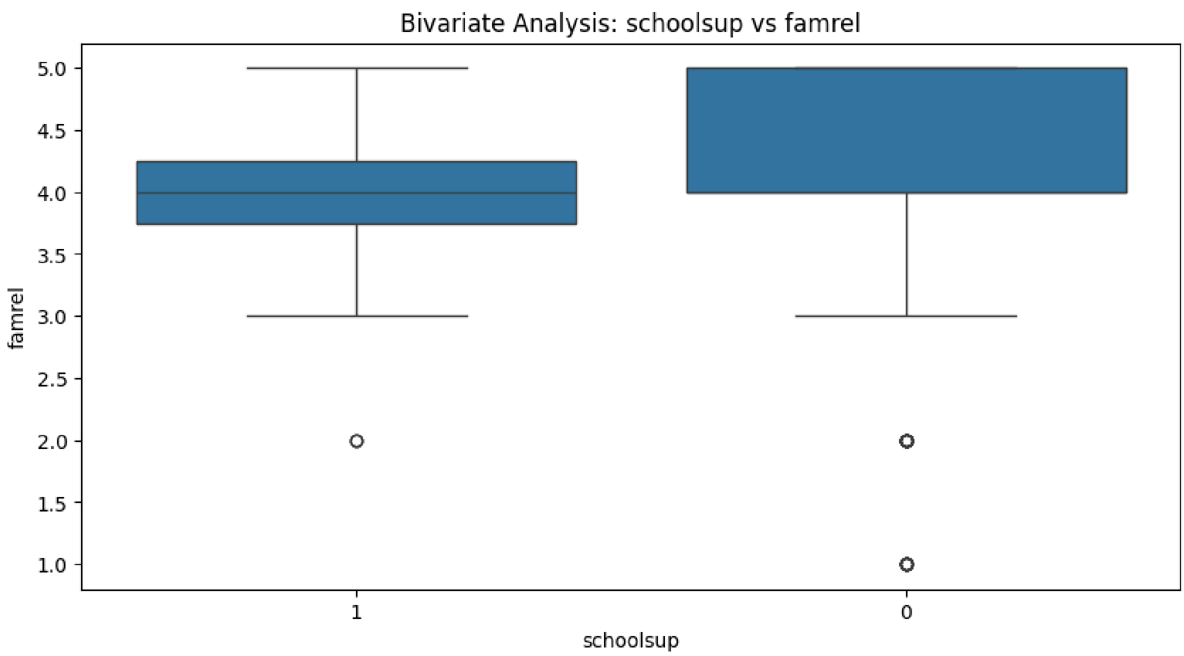

Bivariate Analysis: schoolsup vs Medu
Medu
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
1
0
schoolsup

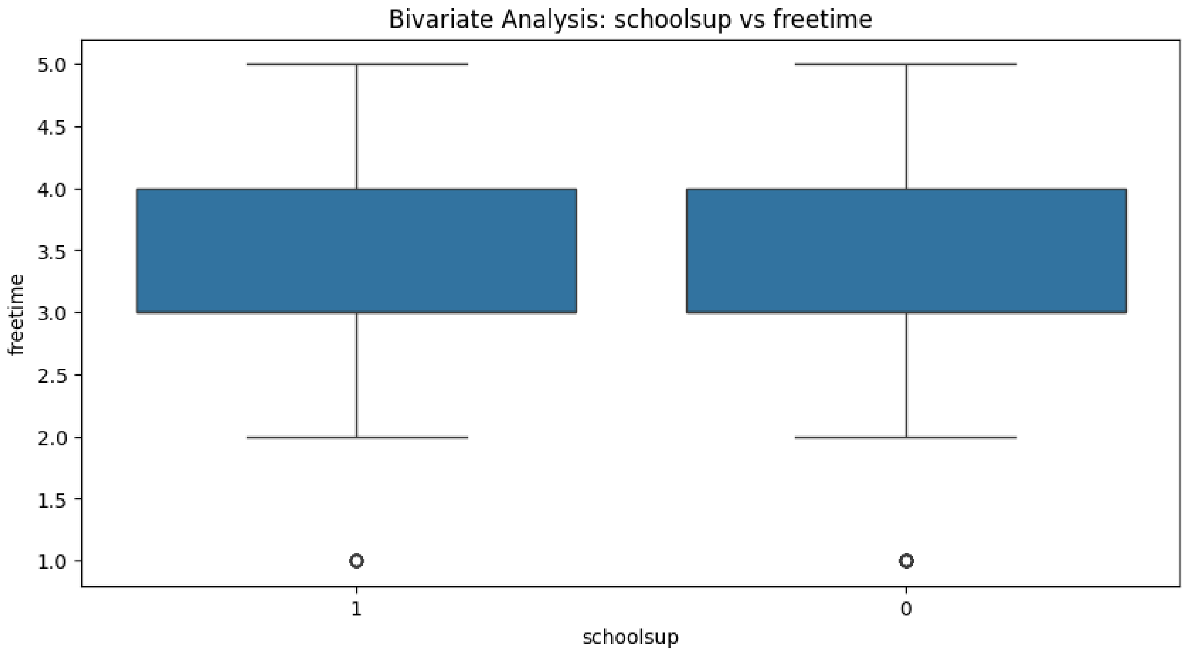

Bivariate Analysis: schoolsup vs Fedu
Fedu
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
1
0
schoolsup

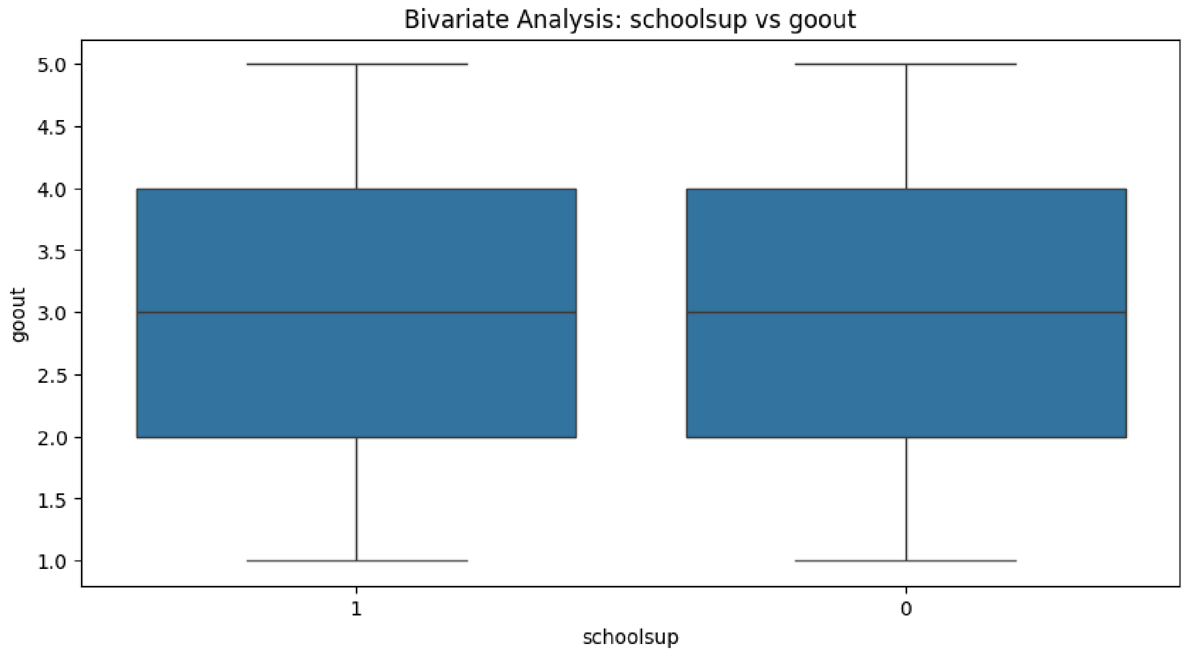

Bivariate Analysis: schoolsup vs traveltime
traveltime
4.0
3.5
3.0
2.5
2.0
1.5
1.0
1
0
schoolsup

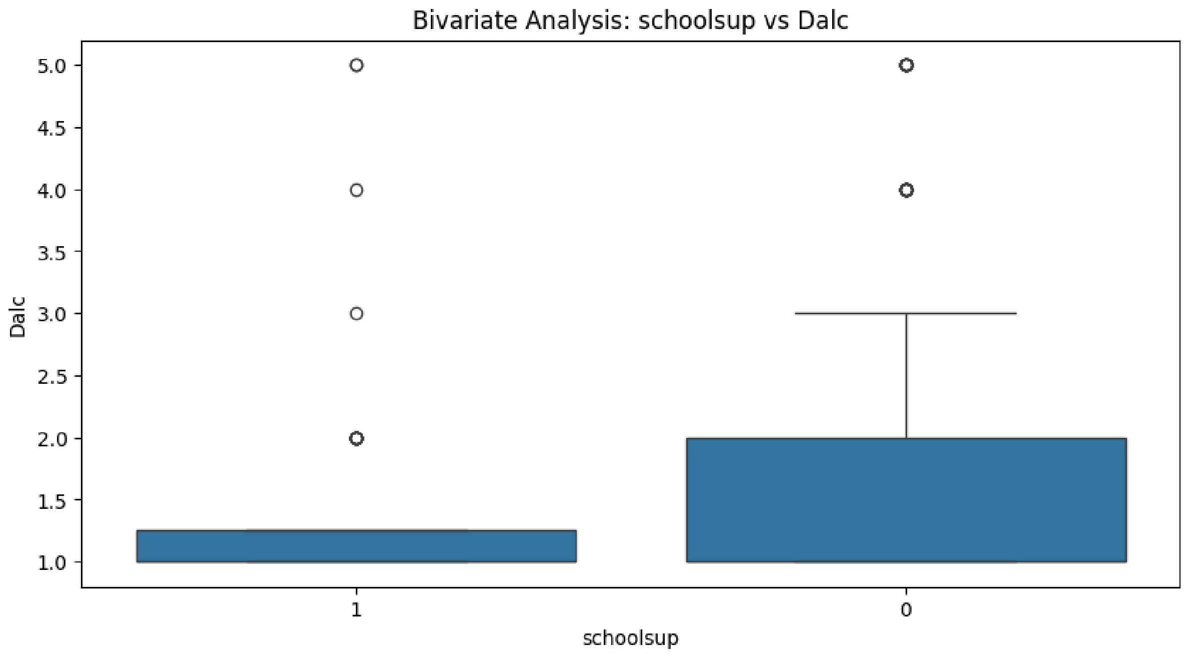

Bivariate Analysis: schoolsup vs studytime
studytime
4.0
3.5
3.0
2.5
2.0
1.5
1.0
1
0
schoolsup

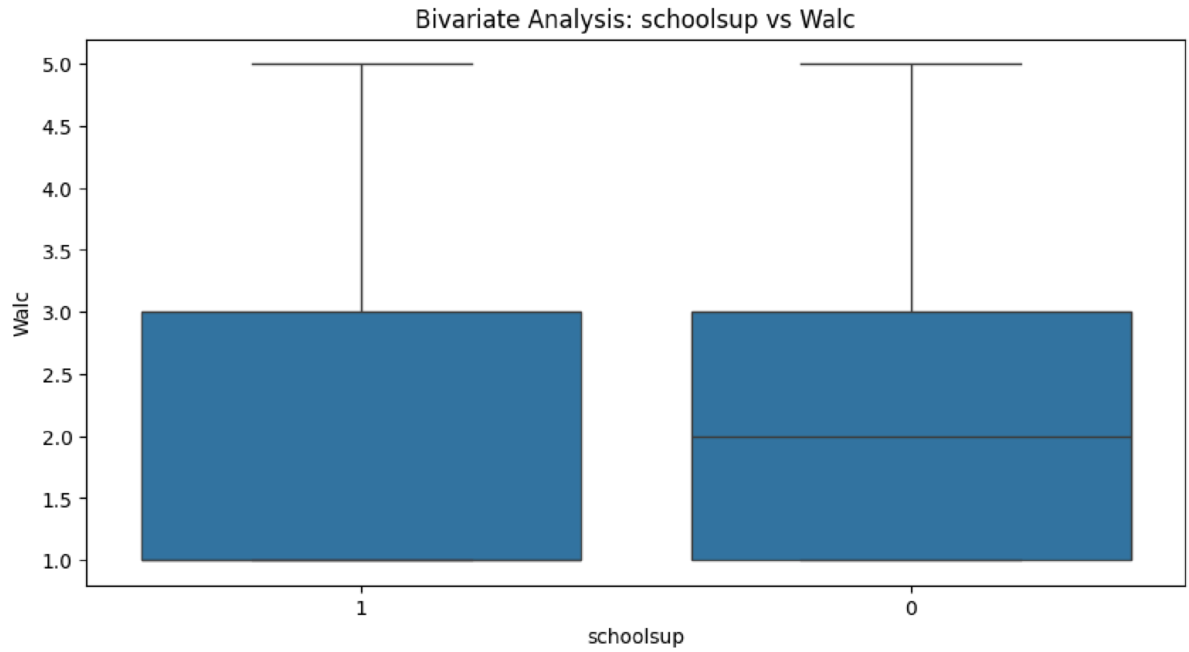

Bivariate Analysis: schoolsup vs failures
failures
3.0
2.5
2.0
1.5
1.0
0.5
0.0
1
0
schoolsup

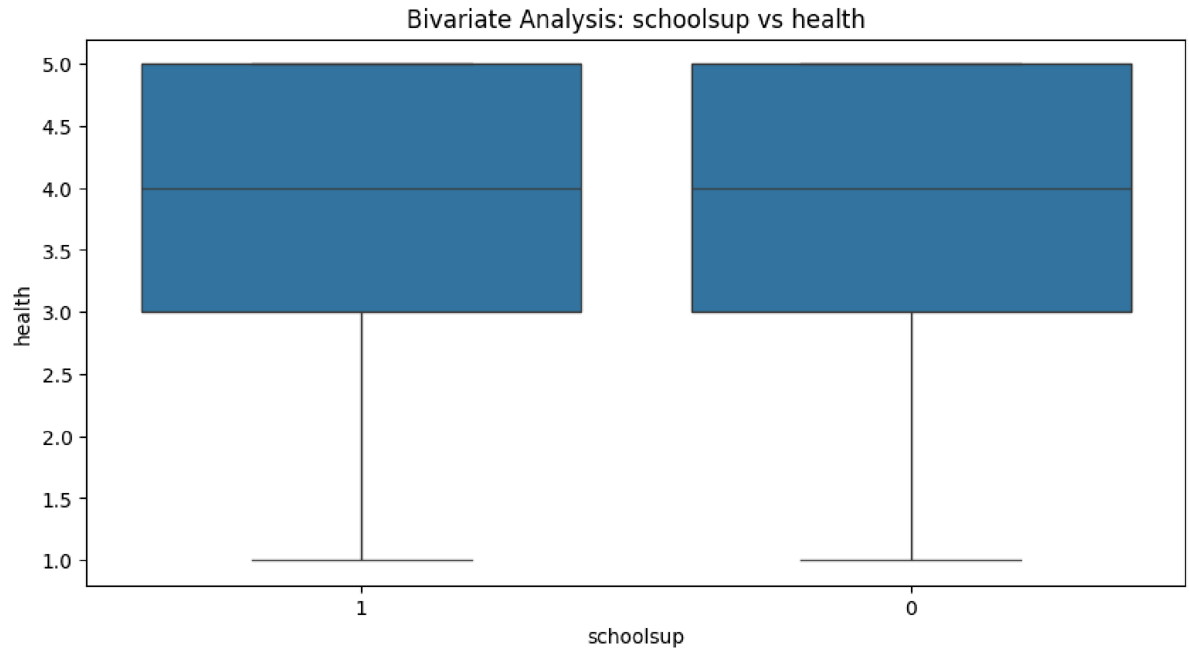

Bivariate Analysis: schoolsup vs famrel
famrel
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
1
0
schoolsup

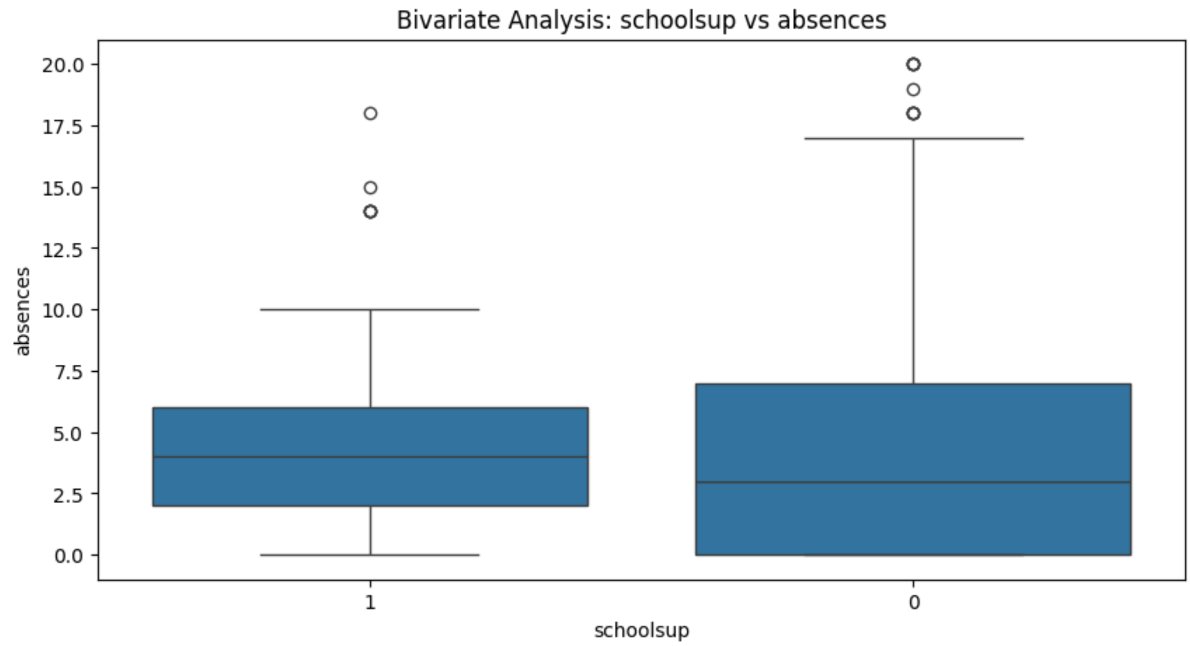

Bivariate Analysis: schoolsup vs freetime
freetime
schoolsup
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
1
0

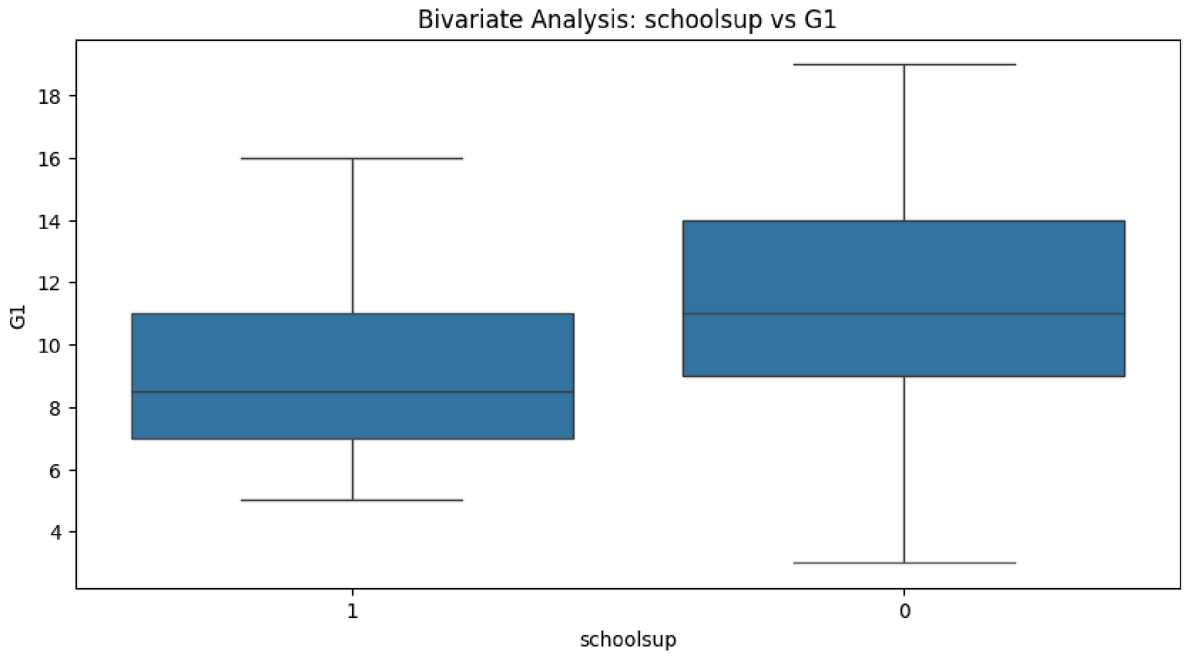

Bivariate Analysis: schoolsup vs goout
goout
schoolsup
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
1
0

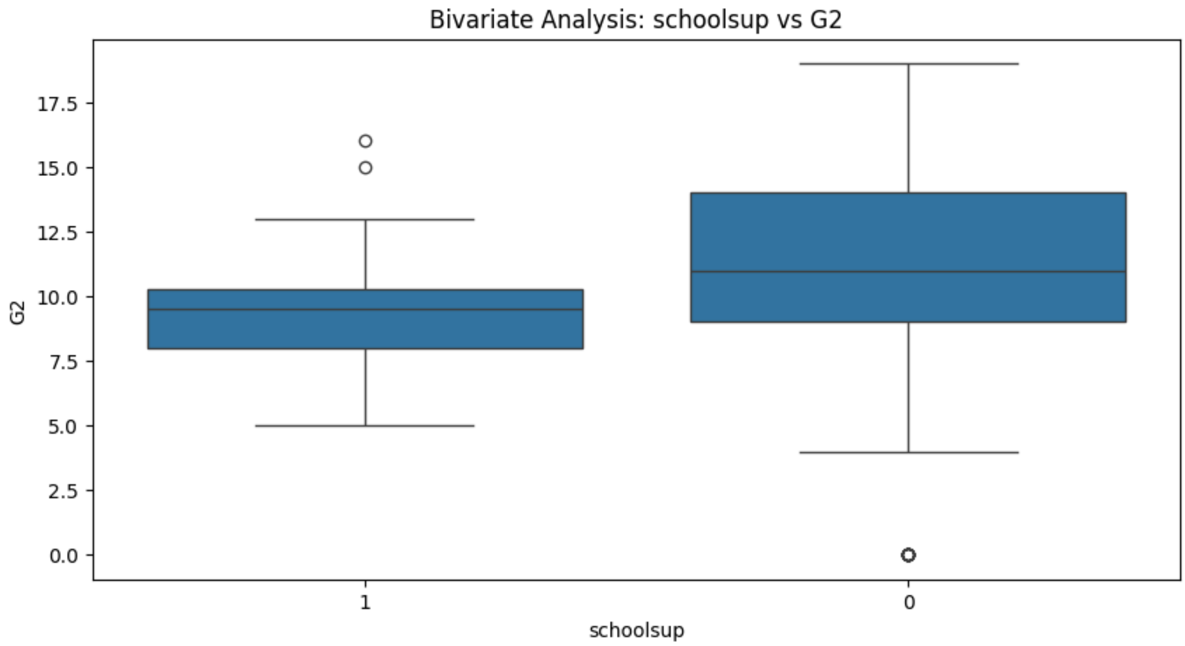

Bivariate Analysis: schoolsup vs Dalc
Dalc
schoolsup
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
1
0

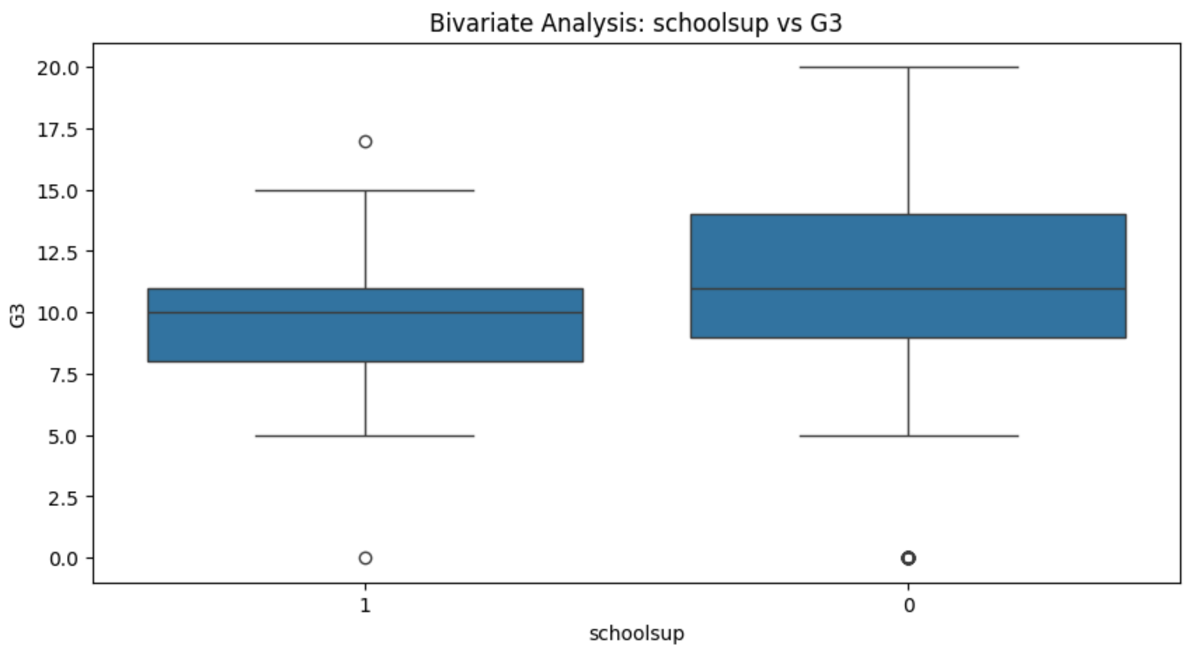

Bivariate Analysis: schoolsup vs Walc
Walc
schoolsup
1
0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0


Bivariate Analysis: schoolsup vs health
health
schoolsup
1
0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0


Bivariate Analysis: schoolsup vs absences
absences
schoolsup
1
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

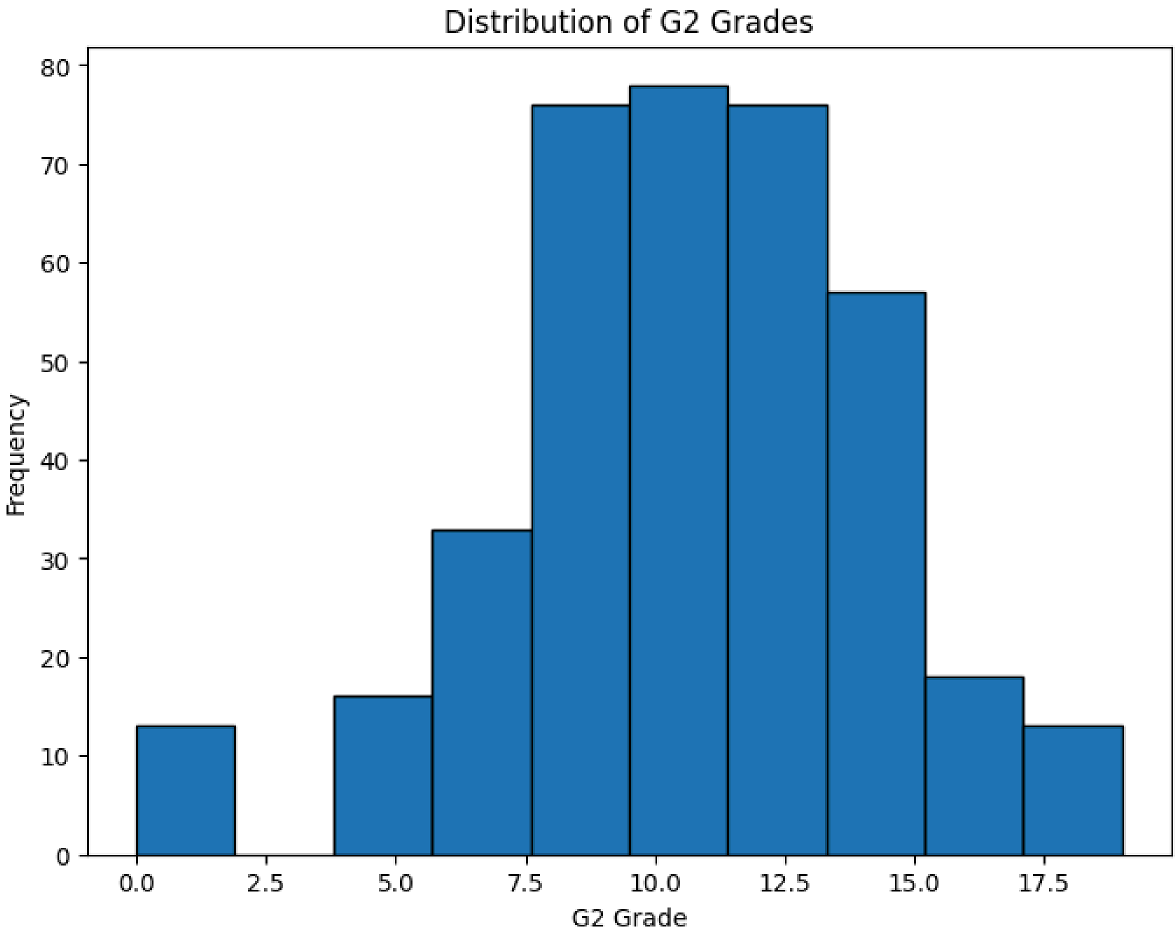




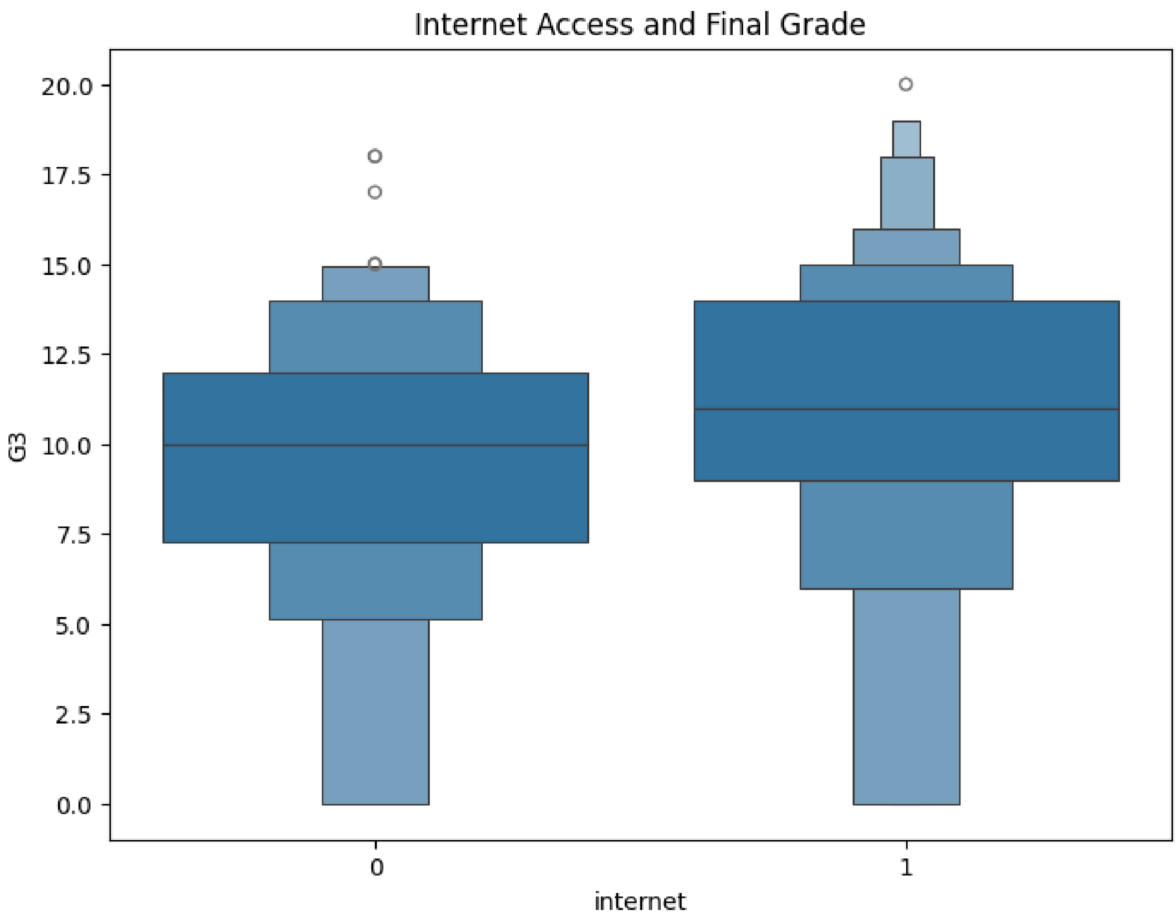



```
Column 'age_group' not found in DataFrame, skipping.
```

In [18]:
```python
# Histogram of G2 grades
plt.figure(figsize=(8, 6))
plt.hist(df['G2'], bins=10, edgecolor='black')
plt.title('Distribution of G2 Grades')
plt.xlabel('G2 Grade')
plt.ylabel('Frequency')
plt.show()
```

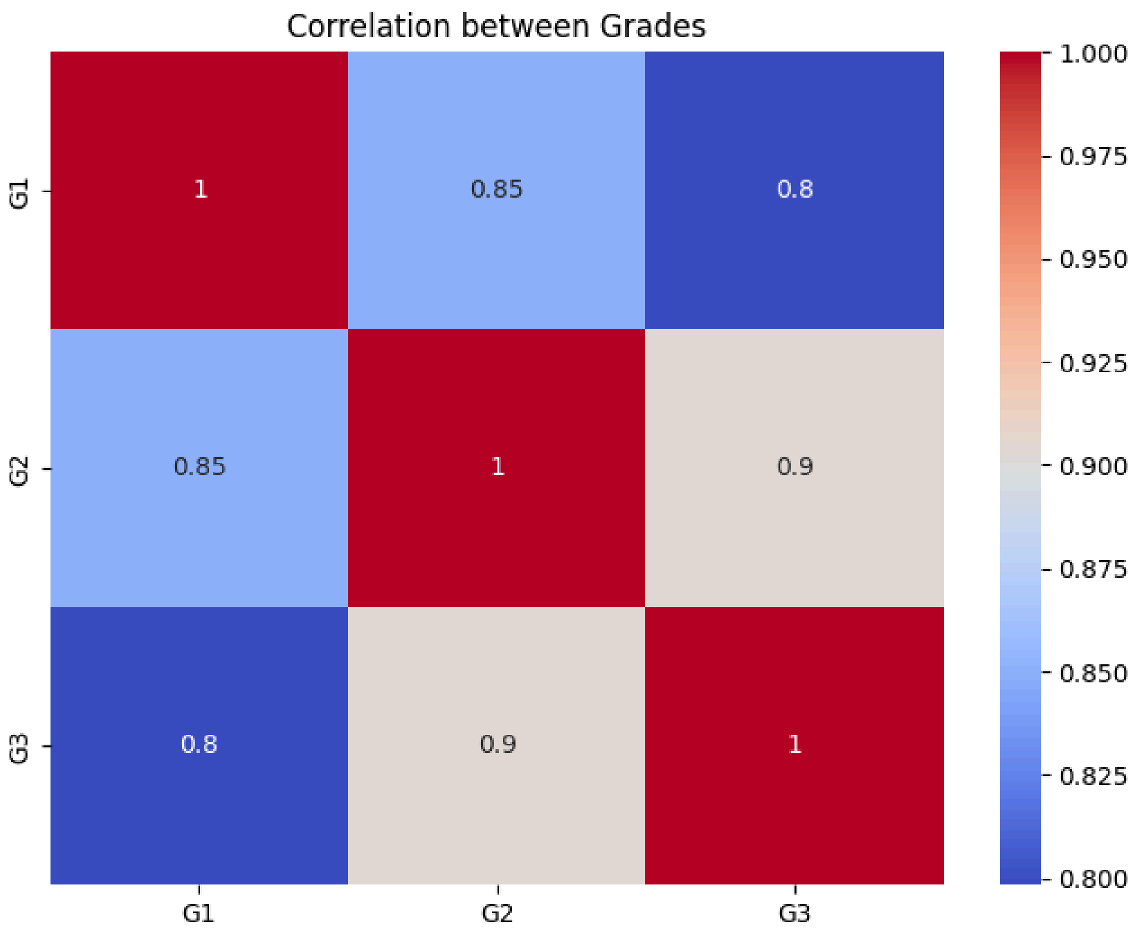


In [19]:
```python
# Relationship between internet access and final grade
plt.figure(figsize=(8, 6))
sns.boxplot(x='internet', y='G3', data=df)  # Using boxplot for better visualization of
plt.title('Internet Access and Final Grade')
plt.show()
```

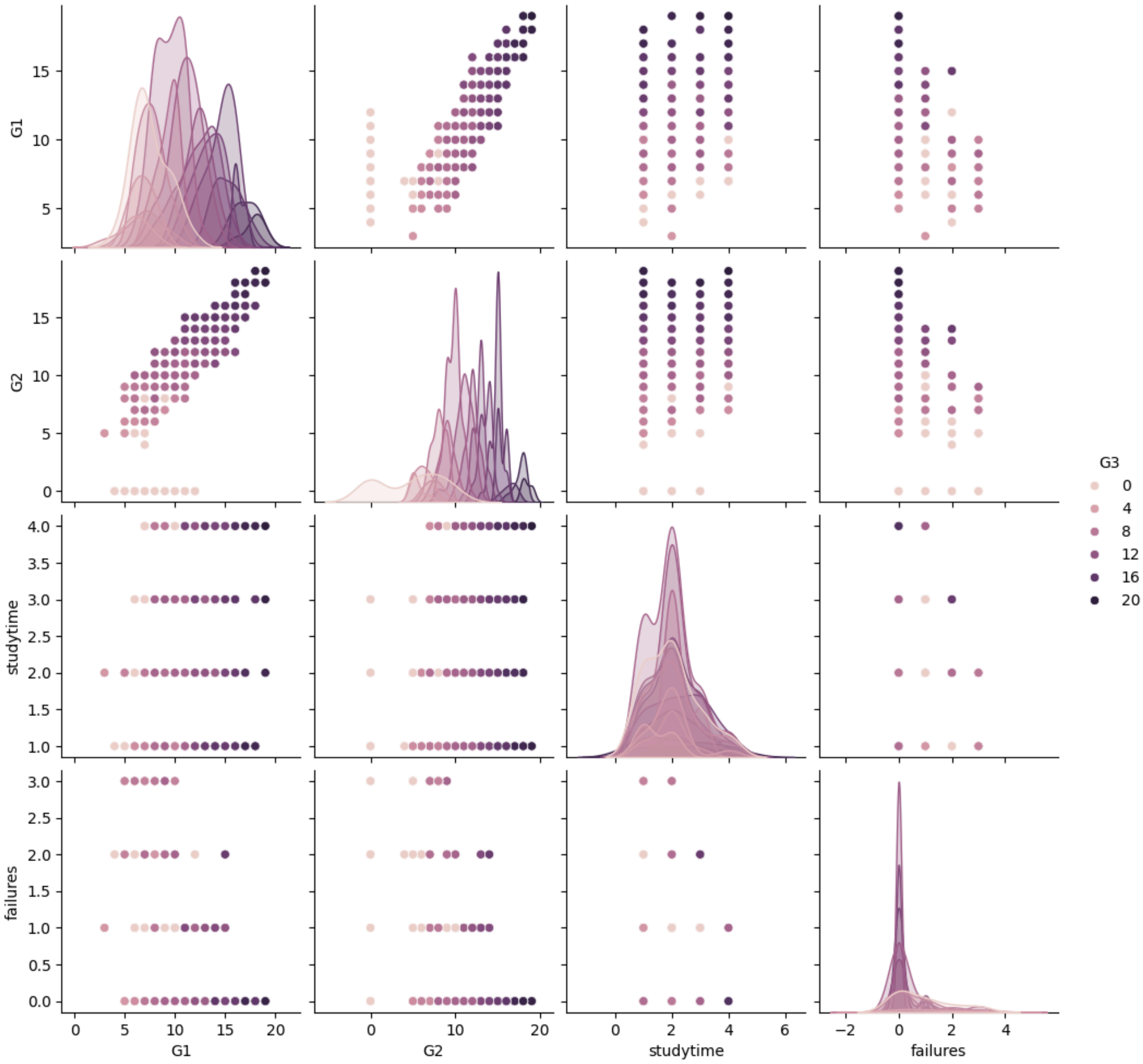


Multivariate Analysis

In [20]:
```
# Heatmap of correlations between grades
plt.figure(figsize=(8, 6))
sns.heatmap(df[['G1', 'G2', 'G3']].corr(), annot=True, cmap='coolwarm')
plt.title('Correlation between Grades')
plt.show()
```

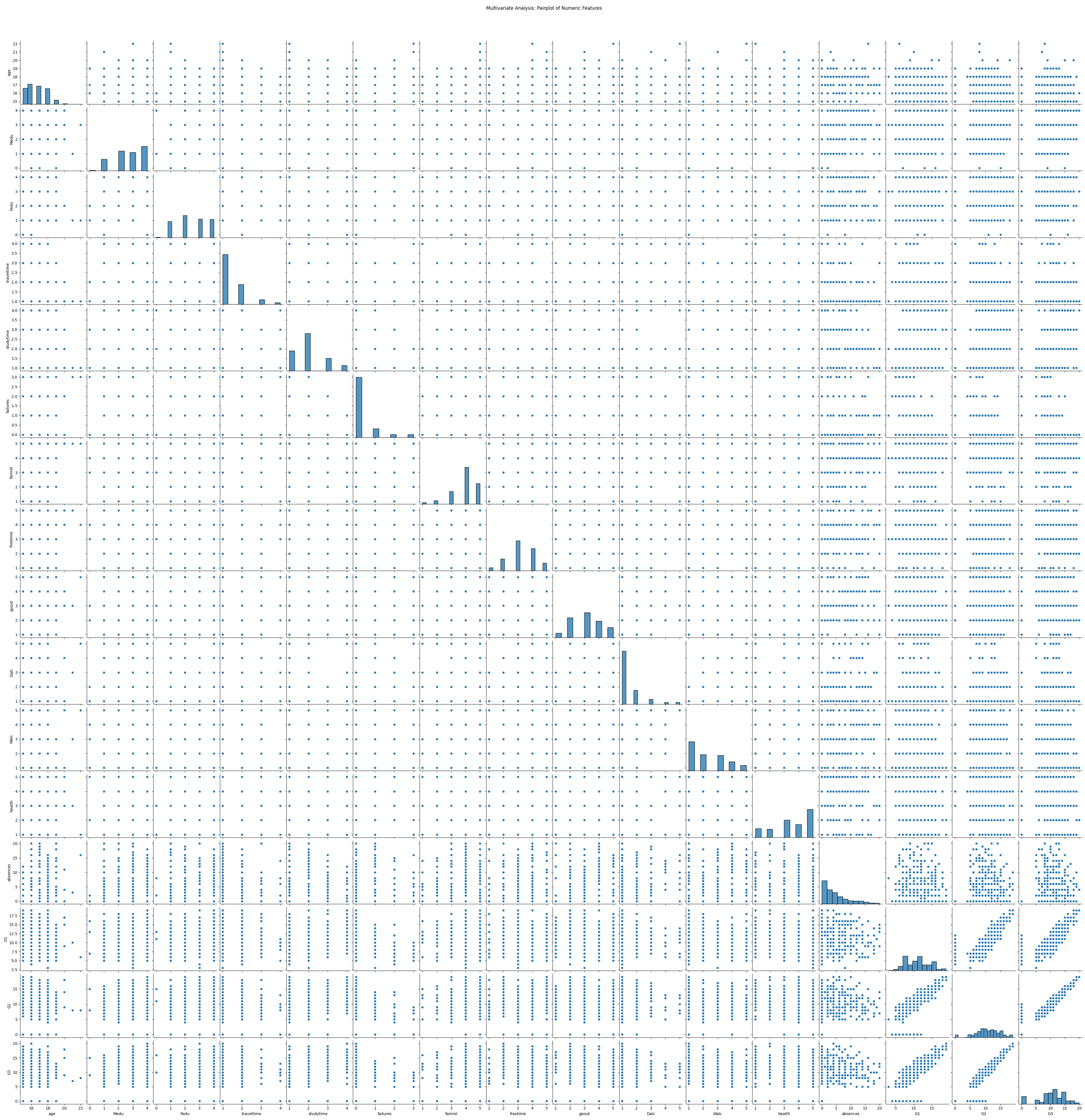


In [21]:
```
# Pairplot of relevant features
sns.pairplot(df[['G1', 'G2', 'G3', 'studytime', 'failures']], hue='G3')
plt.show()
```

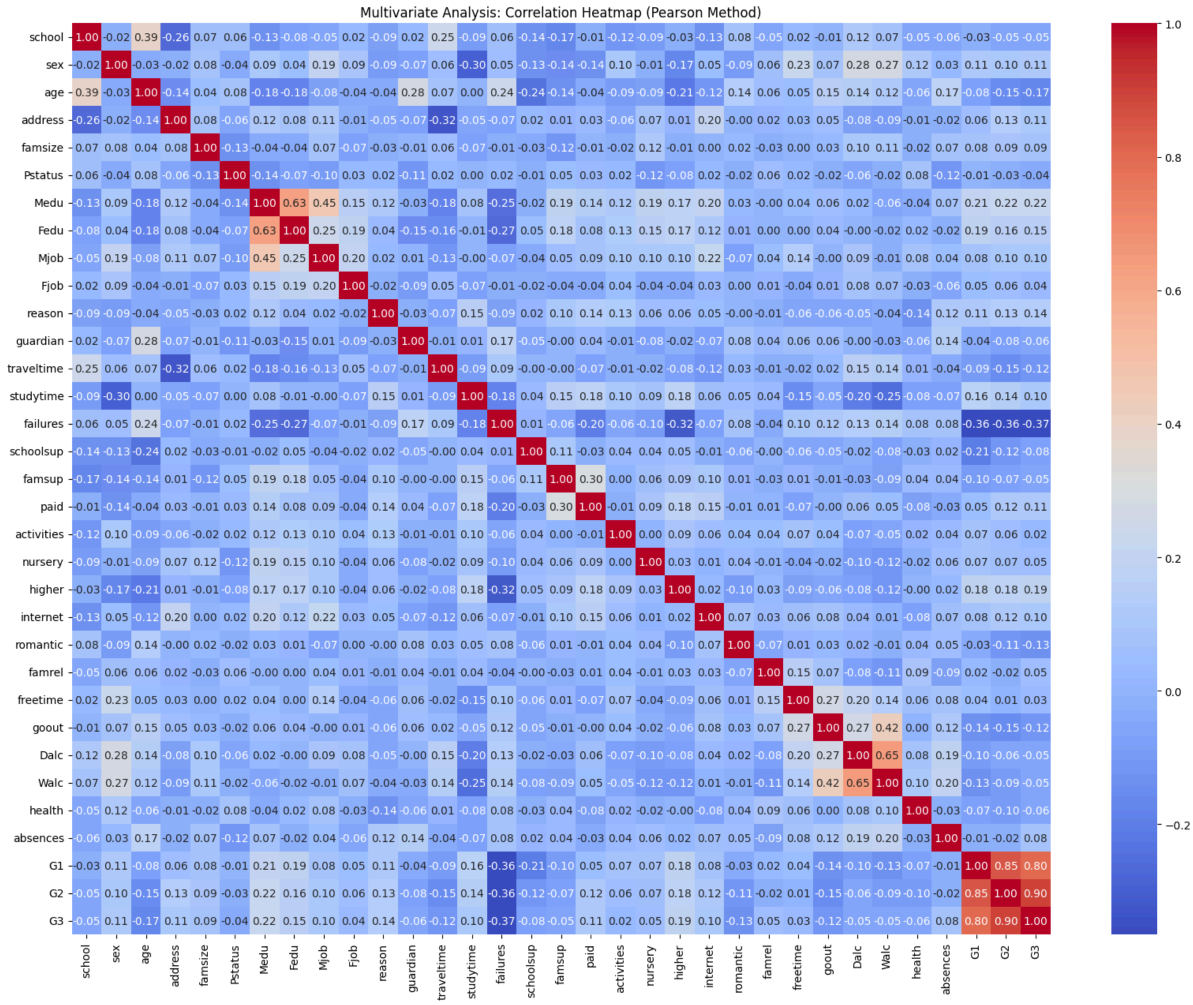


In [22]:
```
# Multivariate Analysis
plt.figure(figsize=(12,6))
sns.pairplot(df.select_dtypes(include=['float64', 'int64']))
plt.suptitle('Multivariate Analysis: Pairplot of Numeric Features', y=1.02)
plt.show()
```

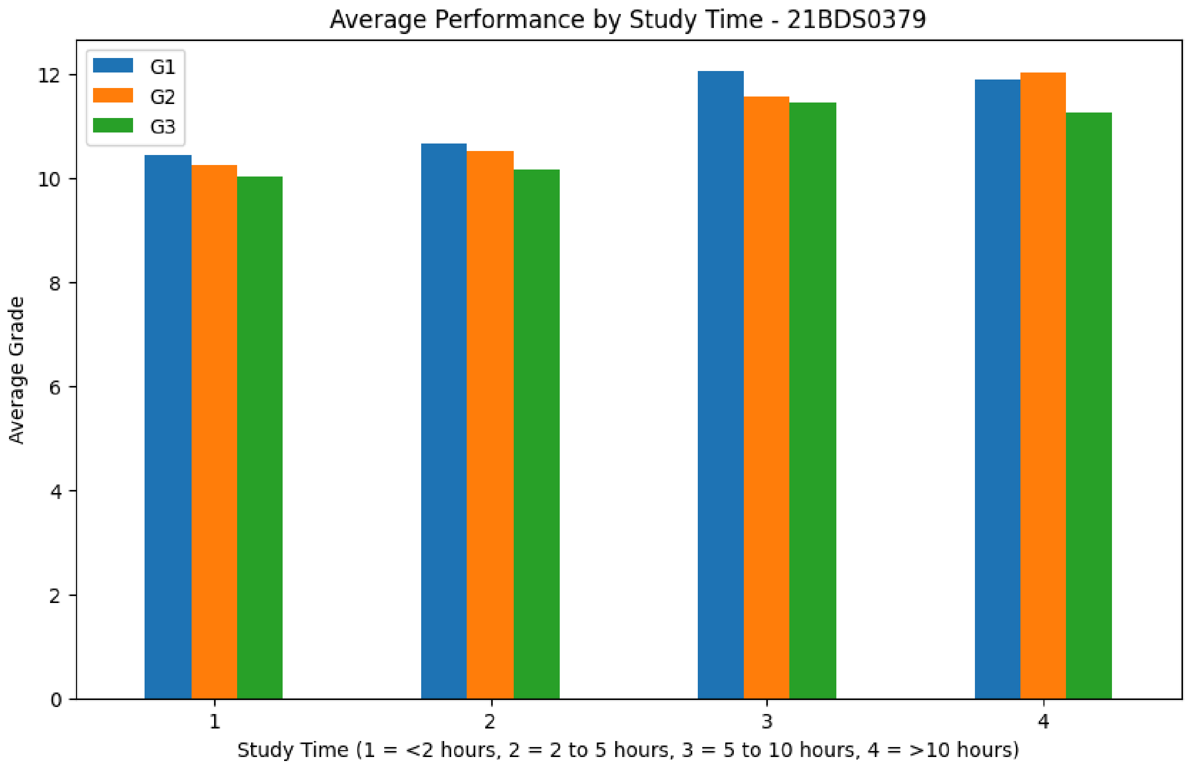
```
<Figure size 1200x600 with 0 Axes>
```



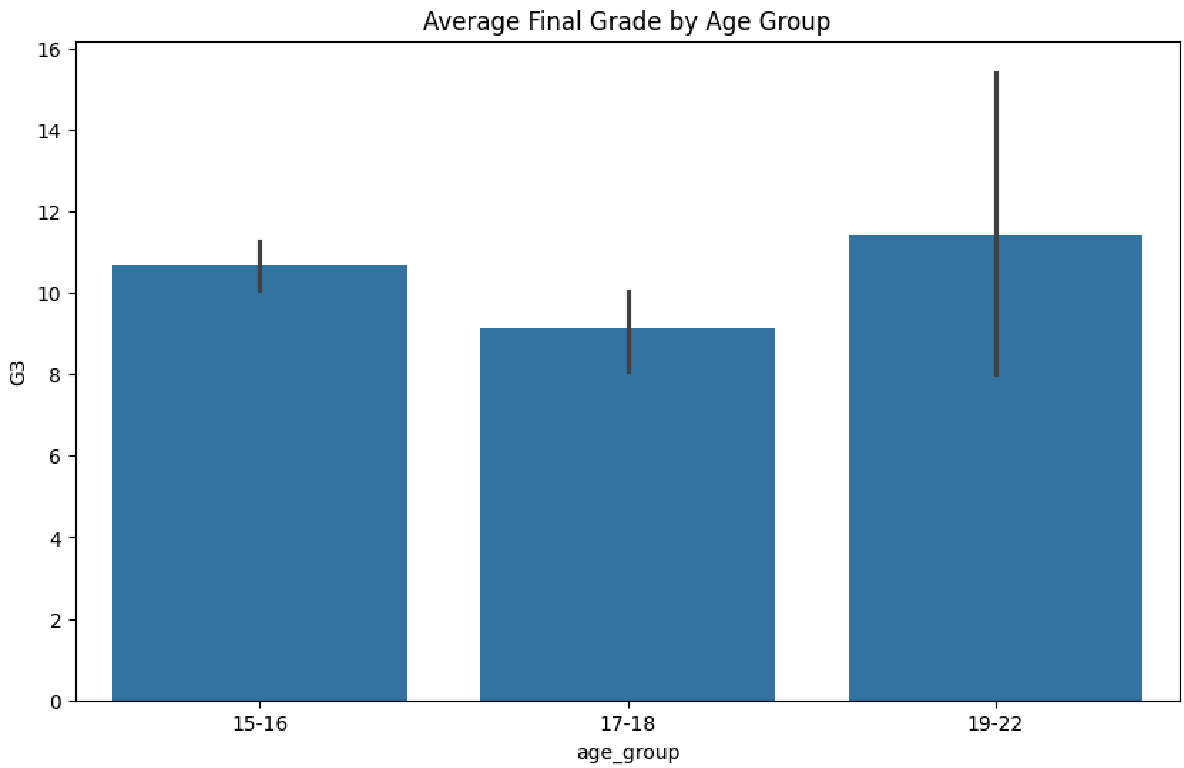
In [23]:
```
#Correlation Matrix with Heatmap using Pearson method
plt.figure(figsize=(20,15))
sns.heatmap(df.corr(method='pearson'), annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Multivariate Analysis: Correlation Heatmap (Pearson Method)')
plt.show()
```



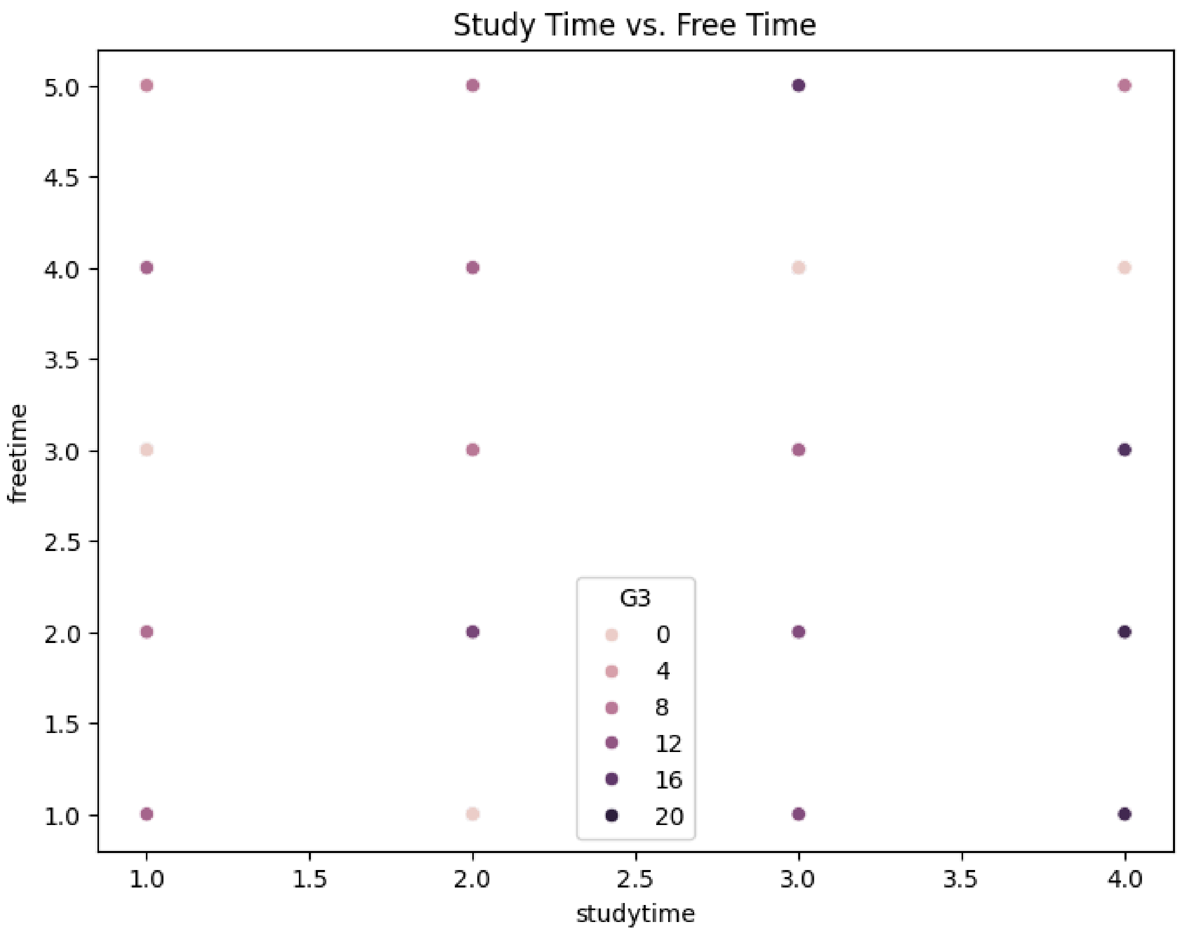
In [24]:
```python
# Bar Plot - Average Performance (G1, G2, G3) by Study Time
data = pd.read_csv('MyDataset_EDA.csv')
study_time_avg_performance = df.groupby('studytime')[['G1', 'G2', 'G3']].mean()

study_time_avg_performance.plot(kind='bar', figsize=(10,6))
plt.title("Average Performance by Study Time - 21BDS0379")
plt.xlabel("Study Time (1 = <2 hours, 2 = 2 to 5 hours, 3 = 5 to 10 hours, 4 = >10 hours)")
plt.ylabel("Average Grade")
plt.xticks(rotation=0)
plt.show()
```



In [25]:
```
# Bar plot of average G3 by age group
df['age_group'] = pd.cut(df['age'], bins=[15, 17, 19, 22], labels=['15-16', '17-18', '19-22
plt.figure(figsize=(10,6))
sns.barplot(x='age_group', y='G3', data=df)
plt.title('Average Final Grade by Age Group')
plt.show()
```

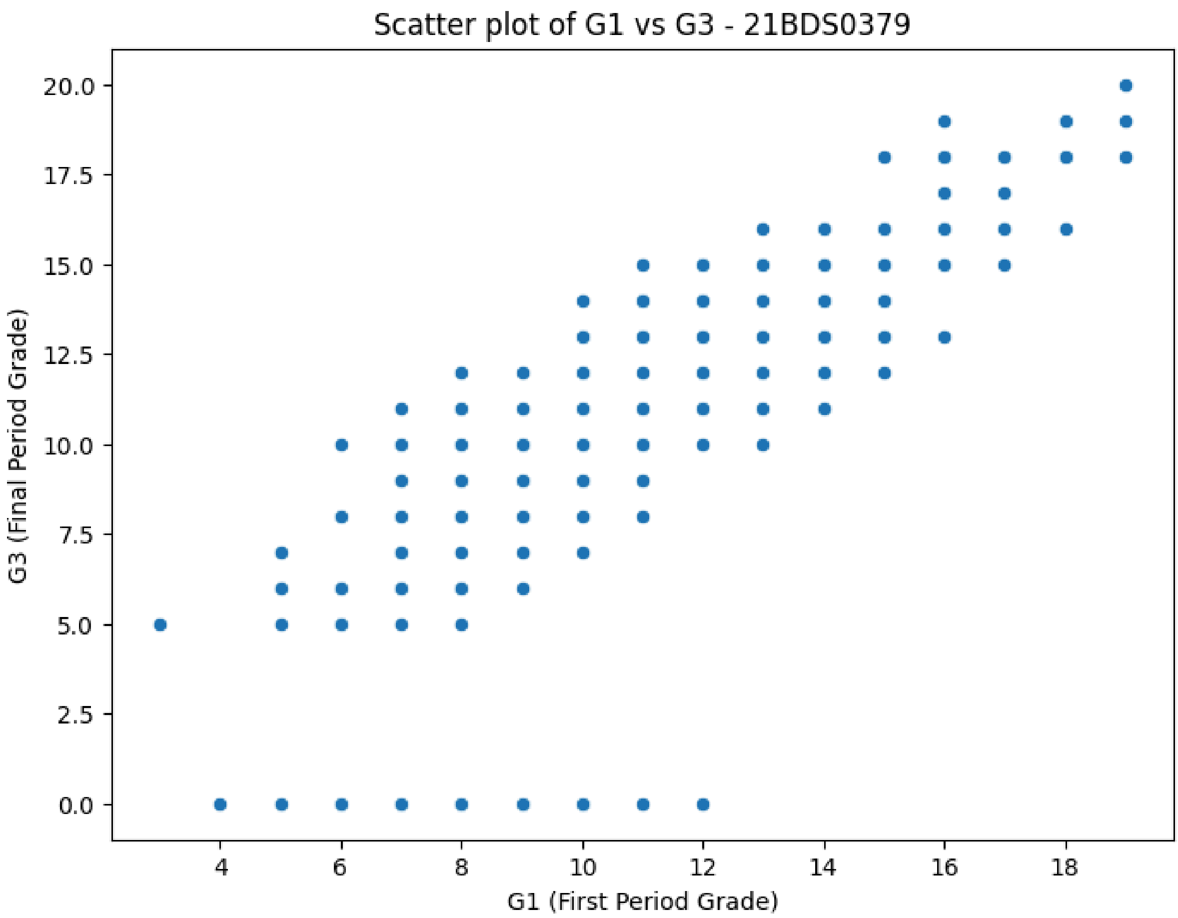


In [26]:
```
# Scatter plot of study time vs free time
plt.figure(figsize=(8, 6))
sns.scatterplot(x='studytime', y='freetime', data=df, hue='G3')
plt.title('Study Time vs. Free Time')
plt.show()
```



In [27]:

```
# Scatter Plot - G1 vs G3
plt.figure(figsize=(8,6))
sns.scatterplot(x=df['G1'], y=df['G3'])
plt.title("Scatter plot of G1 vs G3 - 21BDS0379")
plt.xlabel("G1 (First Period Grade)")
plt.ylabel("G3 (Final Period Grade)")
plt.show()
```



PHASE 2

MODULE 4

In [28]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [29]:
```
# Statistical summary measures for the numerical data
stat_summary = df.describe()
print("Statistical Summary Measures:")
print(stat_summary)

# Data elaboration - Checking the data types and null values
data_info = data.info()
null_values = data.isnull().sum()

print("\nData Information:")
print(data_info)
print("\nMissing Values Count:")
print(null_values)
```

```
Statistical Summary Measures:
           school         sex         age     address     famsize     Pstatus  \
count  380.000000  380.000000  380.000000  380.000000  380.000000  380.000000   
mean     0.121053    0.478947   16.671053    1.763158    0.289474    1.868421   
std      0.326618    0.500215    1.274762    0.437926    0.454116    0.382400   
min      0.000000    0.000000   15.000000    0.000000    0.000000    0.000000   
25%      0.000000    0.000000   16.000000    2.000000    0.000000    2.000000   
50%      0.000000    0.000000   17.000000    2.000000    0.000000    2.000000   
75%      0.000000    1.000000   18.000000    2.000000    1.000000    2.000000   
max      1.000000    1.000000   22.000000    2.000000    1.000000    2.000000   

             Medu        Fedu        Mjob        Fjob  ...      famrel  \
count  380.000000  380.000000  380.000000  380.000000  ...  380.000000   
mean     2.726316    2.507895    2.155263    2.271053  ...    3.947368   
std      1.101135    1.093247    1.234764    0.870328  ...    0.905782   
min      0.000000    0.000000    0.000000    0.000000  ...    1.000000   
25%      2.000000    2.000000    2.000000    2.000000  ...    4.000000   
50%      3.000000    2.000000    2.000000    2.000000  ...    4.000000   
75%      4.000000    3.000000    3.000000    3.000000  ...    5.000000   
max      4.000000    4.000000    4.000000    4.000000  ...    5.000000   

         freetime       goout        Dalc        Walc      health    absences  \
count  380.000000  380.000000  380.000000  380.000000  380.000000  380.000000   
mean     3.260526    3.107895    1.481579    2.278947    3.571053    4.602632   
std      0.984320    1.111912    0.899826    1.289732    1.381256    4.968236   
min      1.000000    1.000000    1.000000    1.000000    1.000000    0.000000   
25%      3.000000    2.000000    1.000000    1.000000    3.000000    0.000000   
50%      3.000000    3.000000    1.000000    2.000000    4.000000    3.000000   
75%      4.000000    4.000000    2.000000    3.000000    5.000000    7.000000   
max      5.000000    5.000000    5.000000    5.000000    5.000000   20.000000   

               G1          G2          G3  
count  380.000000  380.000000  380.000000  
mean    10.921053   10.723684   10.421053  
std      3.312896    3.772553    4.612313  
min      3.000000    0.000000    0.000000  
25%      8.000000    9.000000    8.000000  
50%     11.000000   11.000000   11.000000  
75%     13.000000   13.000000   14.000000  
max     19.000000   19.000000   20.000000  

[8 rows x 33 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 395 entries, 0 to 394
Data columns (total 33 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   school      395 non-null    object
 1   sex         393 non-null    object
 2   age         395 non-null    int64 
 3   address     394 non-null    object
 4   famsize     394 non-null    object
 5   Pstatus     395 non-null    object
 6   Medu        395 non-null    int64 
 7   Fedu        395 non-null    int64 
 8   Mjob        395 non-null    object
 9   Fjob        395 non-null    object
 10  reason      395 non-null    object
 11  guardian    395 non-null    object
 12  traveltime  395 non-null    int64 
 13  studytime   395 non-null    int64 
 14  failures    395 non-null    int64 
 15  schoolsup   393 non-null    object
 16  famsup      395 non-null    object
 17  paid        395 non-null    object
 18  activities  395 non-null    object
 19  nursery     395 non-null    object
```

```
 20  higher      395 non-null    object
 21  internet    395 non-null    object
 22  romantic    395 non-null    object
 23  famrel      395 non-null    int64
 24  freetime    395 non-null    int64
 25  goout       395 non-null    int64
 26  Dalc        395 non-null    int64
 27  Walc        395 non-null    int64
 28  health      395 non-null    int64
 29  absences    395 non-null    int64
 30  G1          395 non-null    int64
 31  G2          395 non-null    int64
 32  G3          395 non-null    int64
dtypes: int64(16), object(17)
memory usage: 102.0+ KB

Data Information:
None

Missing Values Count:
school        0
sex           2
age           0
address       1
famsize       1
Pstatus       0
Medu          0
Fedu          0
Mjob          0
Fjob          0
reason        0
guardian      0
traveltime    0
studytime     0
failures      0
schoolsup     2
famsup        0
paid          0
activities    0
nursery       0
higher        0
internet      0
romantic      0
famrel        0
freetime      0
goout         0
Dalc          0
Walc          0
health        0
absences      0
G1            0
G2            0
G3            0
dtype: int64
```

In [30]:

```
# 1-D Statistical Data Analysis: Distribution of 'age'
age_stats = df['age'].describe()
print("\n1-D Statistical Data Analysis (Age):")
print(age_stats)
```

```
1-D Statistical Data Analysis (Age):
count    380.000000
mean      16.671053
std        1.274762
min       15.000000
25%       16.000000
50%       17.000000
75%       18.000000
max       22.000000
Name: age, dtype: float64
```

In [31]:

```
# 2-D Statistical Data Analysis: Correlation matrix for numerical variables
numeric_data = data.select_dtypes(include=['int64', 'float64'])  # Selecting only numeric c
correlation_matrix = numeric_data.corr()
print("\n2-D Statistical Data Analysis (Correlation Matrix):")
print(correlation_matrix)
```

```
2-D Statistical Data Analysis (Correlation Matrix):
                 age      Medu      Fedu  traveltime  studytime  failures  \
age         1.000000 -0.163658 -0.163438    0.070641  -0.004140  0.243665   
Medu       -0.163658  1.000000  0.623455   -0.171639   0.064944 -0.236680   
Fedu       -0.163438  0.623455  1.000000   -0.158194  -0.009175 -0.250408   
traveltime  0.070641 -0.171639 -0.158194    1.000000  -0.100909  0.092239   
studytime  -0.004140  0.064944 -0.009175   -0.100909   1.000000 -0.173563   
failures    0.243665 -0.236680 -0.250408    0.092239  -0.173563  1.000000   
famrel      0.053940 -0.003914 -0.001370   -0.016808   0.039731 -0.044337   
freetime    0.016434  0.030891 -0.012846   -0.017025  -0.143198  0.091987   
goout       0.126964  0.064094  0.043105    0.028540  -0.063904  0.124561   
Dalc        0.131125  0.019834  0.002386    0.138325  -0.196019  0.136047   
Walc        0.117276 -0.047123 -0.012631    0.134116  -0.253785  0.141962   
health     -0.062187 -0.046878  0.014742    0.007501  -0.075616  0.065827   
absences    0.175230  0.100285  0.024473   -0.012944  -0.062700  0.063726   
G1         -0.064081  0.205341  0.190270   -0.093040   0.160612 -0.354718   
G2         -0.143474  0.215527  0.164893   -0.153198   0.135880 -0.355896   
G3         -0.161579  0.217147  0.152457   -0.117142   0.097820 -0.360415   

              famrel  freetime     goout      Dalc      Walc    health  \
age         0.053940  0.016434  0.126964  0.131125  0.117276 -0.062187   
Medu       -0.003914  0.030891  0.064094  0.019834 -0.047123 -0.046878   
Fedu       -0.001370 -0.012846  0.043105  0.002386 -0.012631  0.014742   
traveltime -0.016808 -0.017025  0.028540  0.138325  0.134116  0.007501   
studytime   0.039731 -0.143198 -0.063904 -0.196019 -0.253785 -0.075616   
failures   -0.044337  0.091987  0.124561  0.136047  0.141962  0.065827   
famrel      1.000000  0.150701  0.064568 -0.077594 -0.113397  0.094056   
freetime    0.150701  1.000000  0.285019  0.209001  0.147822  0.075733   
goout       0.064568  0.285019  1.000000  0.266994  0.420386 -0.009577   
Dalc       -0.077594  0.209001  0.266994  1.000000  0.647544  0.077180   
Walc       -0.113397  0.147822  0.420386  0.647544  1.000000  0.092476   
health      0.094056  0.075733 -0.009577  0.077180  0.092476  1.000000   
absences   -0.044354 -0.058078  0.044302  0.111908  0.136291 -0.029937   
G1          0.022168  0.012613 -0.149104 -0.094159 -0.126179 -0.073172   
G2         -0.018281 -0.013777 -0.162250 -0.064120 -0.084927 -0.097720   
G3          0.051363  0.011307 -0.132791 -0.054660 -0.051939 -0.061335   

            absences        G1        G2        G3  
age         0.175230 -0.064081 -0.143474 -0.161579  
Medu        0.100285  0.205341  0.215527  0.217147  
Fedu        0.024473  0.190270  0.164893  0.152457  
traveltime -0.012944 -0.093040 -0.153198 -0.117142  
studytime  -0.062700  0.160612  0.135880  0.097820  
failures    0.063726 -0.354718 -0.355896 -0.360415  
famrel     -0.044354  0.022168 -0.018281  0.051363  
freetime   -0.058078  0.012613 -0.013777  0.011307  
goout       0.044302 -0.149104 -0.162250 -0.132791  
Dalc        0.111908 -0.094159 -0.064120 -0.054660  
Walc        0.136291 -0.126179 -0.084927 -0.051939  
health     -0.029937 -0.073172 -0.097720 -0.061335  
absences    1.000000 -0.031003 -0.031777  0.034247  
G1         -0.031003  1.000000  0.852118  0.801468  
G2         -0.031777  0.852118  1.000000  0.904868  
G3          0.034247  0.801468  0.904868  1.000000  
```

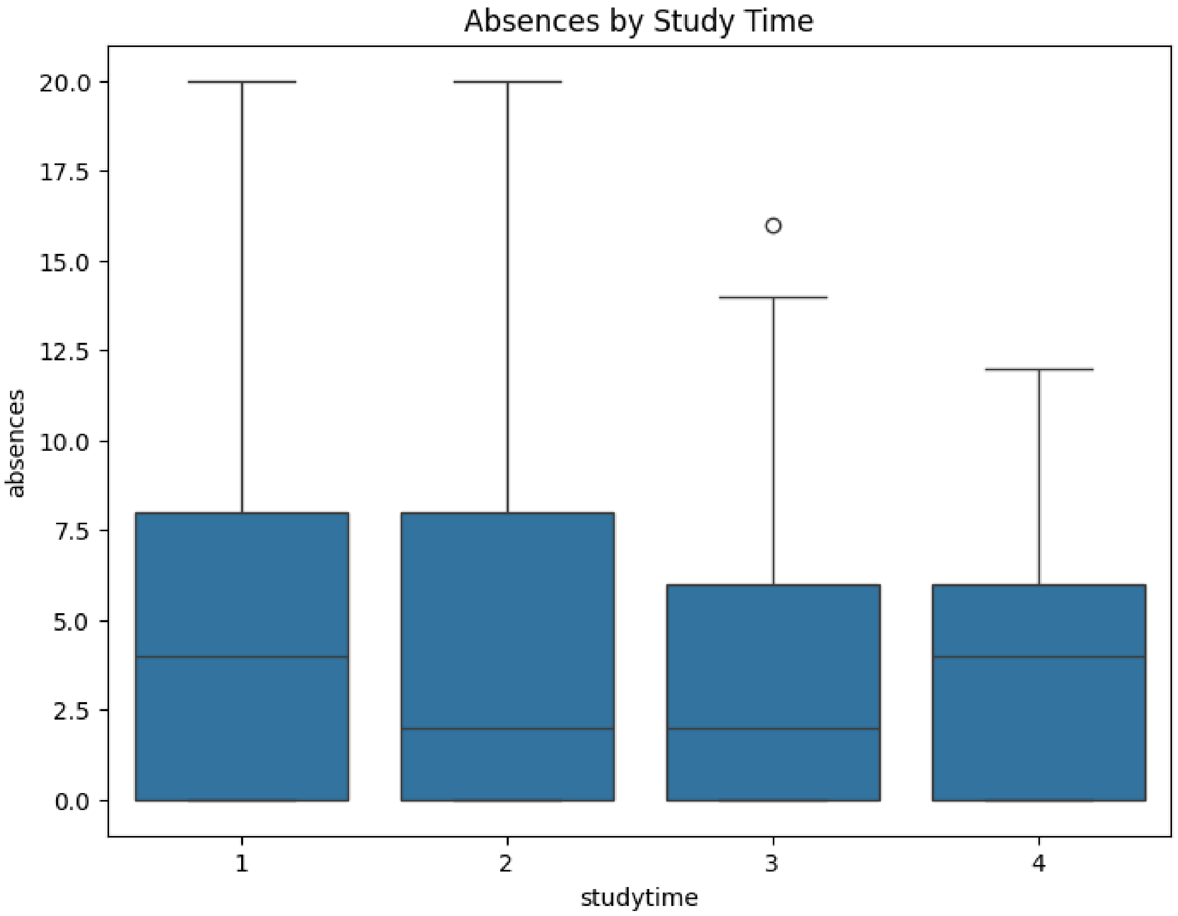
In [32]:

```
# Contingency tables for categorical variables
contingency_sex_address = pd.crosstab(data['sex'], data['address'])
contingency_sex_famsize = pd.crosstab(data['sex'], data['famsize'])

print("\nContingency Table - Sex vs Address:")
print(contingency_sex_address)
print("\nContingency Table - Sex vs Famsize:")
print(contingency_sex_famsize)
```

```
Contingency Table - Sex vs Address:
address  ?   R    U
sex
F        1  44  162
M        1  43  141

Contingency Table - Sex vs Famsize:
famsize  GT3  LE3
sex
F        156   52
M        123   61
```

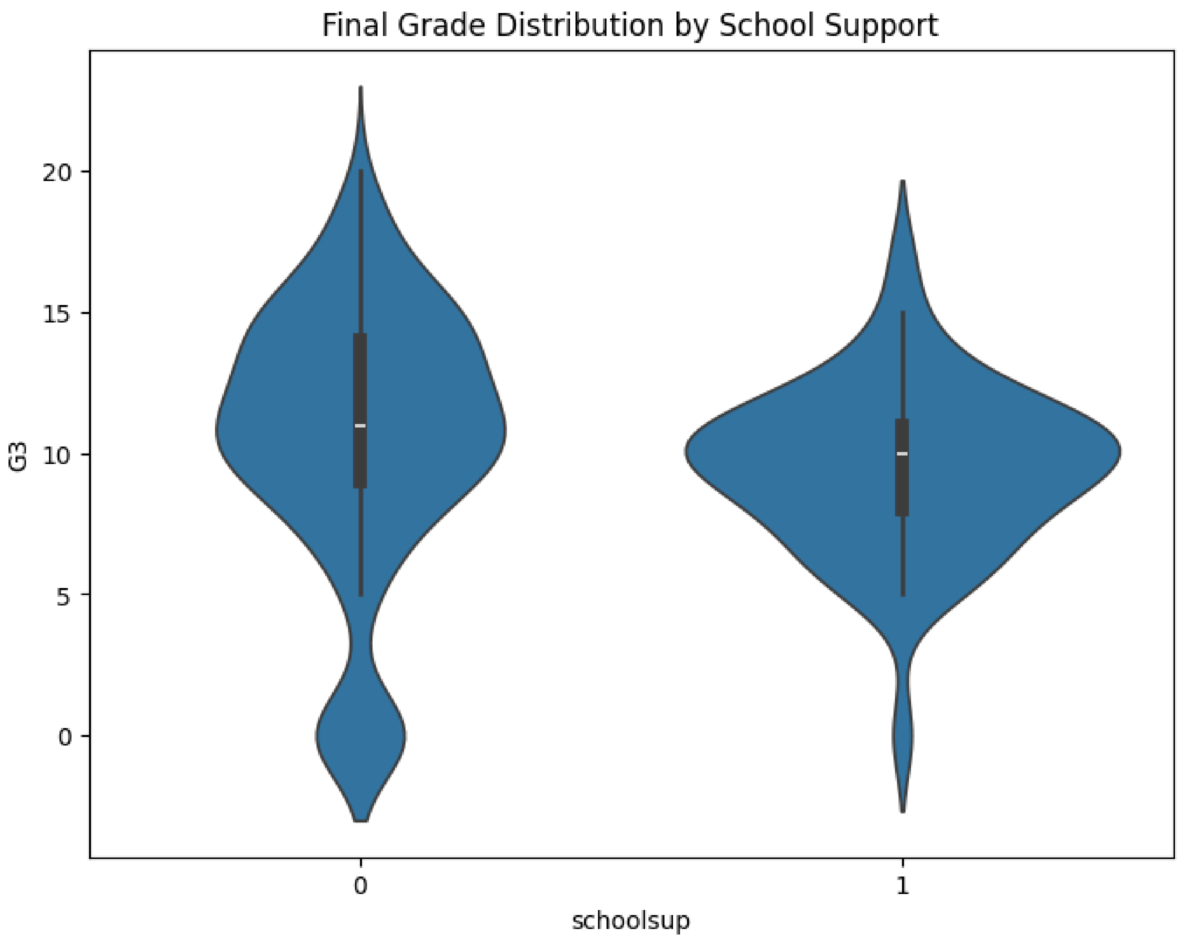
In [33]:

```python
# Box plot of absences by study time
plt.figure(figsize=(8, 6))
sns.boxplot(x='studytime', y='absences', data=df)
plt.title('Absences by Study Time')
plt.show()
```

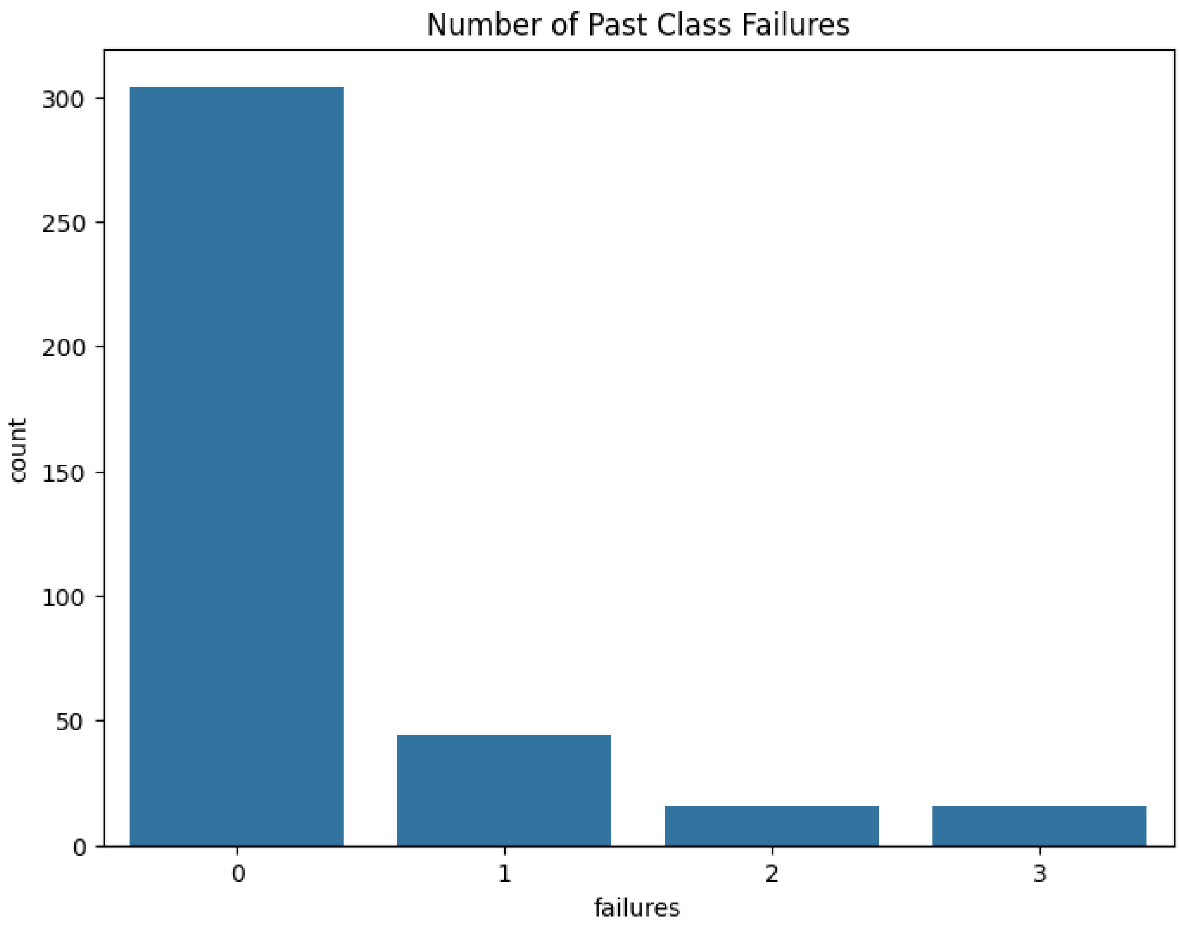


In [34]:

```python
# Violin plot of final grade (G3) by school support
plt.figure(figsize=(8, 6))
sns.violinplot(x='schoolsup', y='G3', data=df)
plt.title('Final Grade Distribution by School Support')
plt.show()
```



In [36]:
```
# Count plot of failures
plt.figure(figsize=(8, 6))
sns.countplot(x='failures', data=df)
plt.title('Number of Past Class Failures')
plt.show()
```



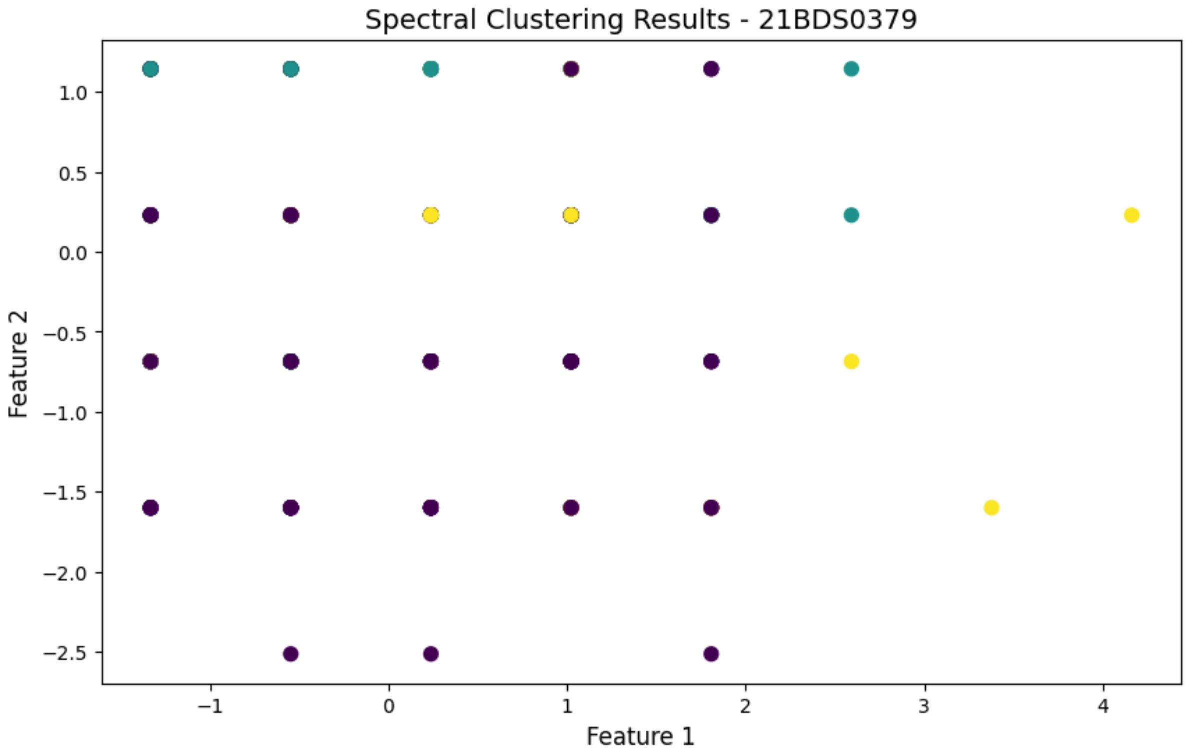
Module 5

In [37]:
```
# Import necessary libraries
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import SpectralClustering, AgglomerativeClustering
from sklearn.mixture import GaussianMixture
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import silhouette_score
from scipy.spatial.distance import pdist, squareform
from sklearn.preprocessing import LabelEncoder
from sklearn.neighbors import kneighbors_graph
```

In [38]:
```
# Load dataset
data = pd.read_csv('MyDataset_EDA.csv')

# Preprocessing: Extracting numerical columns
numerical_data = data.select_dtypes(include=[np.number])

# Standardizing the data
scaler = StandardScaler()
scaled_data = scaler.fit_transform(numerical_data)
```

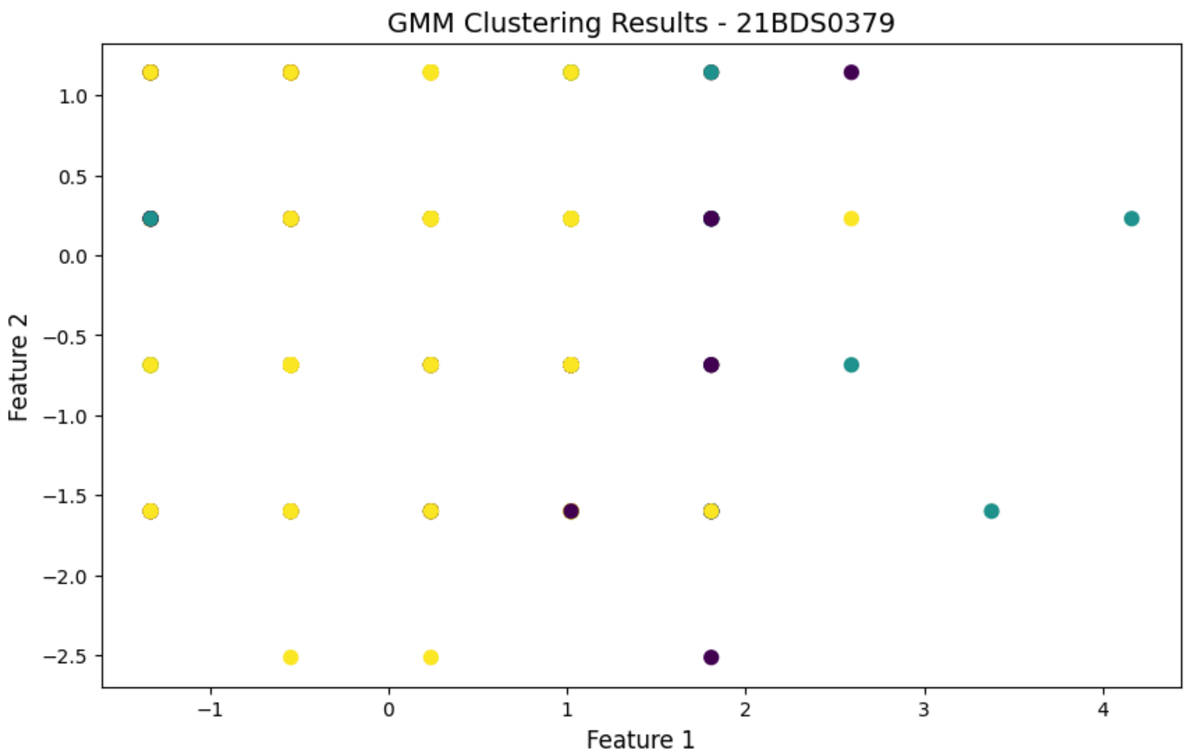
In [39]:
```
# Spectral Clustering
spectral = SpectralClustering(n_clusters=3, affinity='nearest_neighbors', random_state=42)
labels_spectral = spectral.fit_predict(scaled_data)

# Plot Spectral Clustering Results
plt.figure(figsize=(10, 6))
plt.scatter(scaled_data[:, 0], scaled_data[:, 1], c=labels_spectral, cmap='viridis', s=50)
plt.title("Spectral Clustering Results - 21BDS0379", fontsize=14)
plt.xlabel("Feature 1", fontsize=12)
```

```
plt.ylabel("Feature 2", fontsize=12)
plt.show()
```

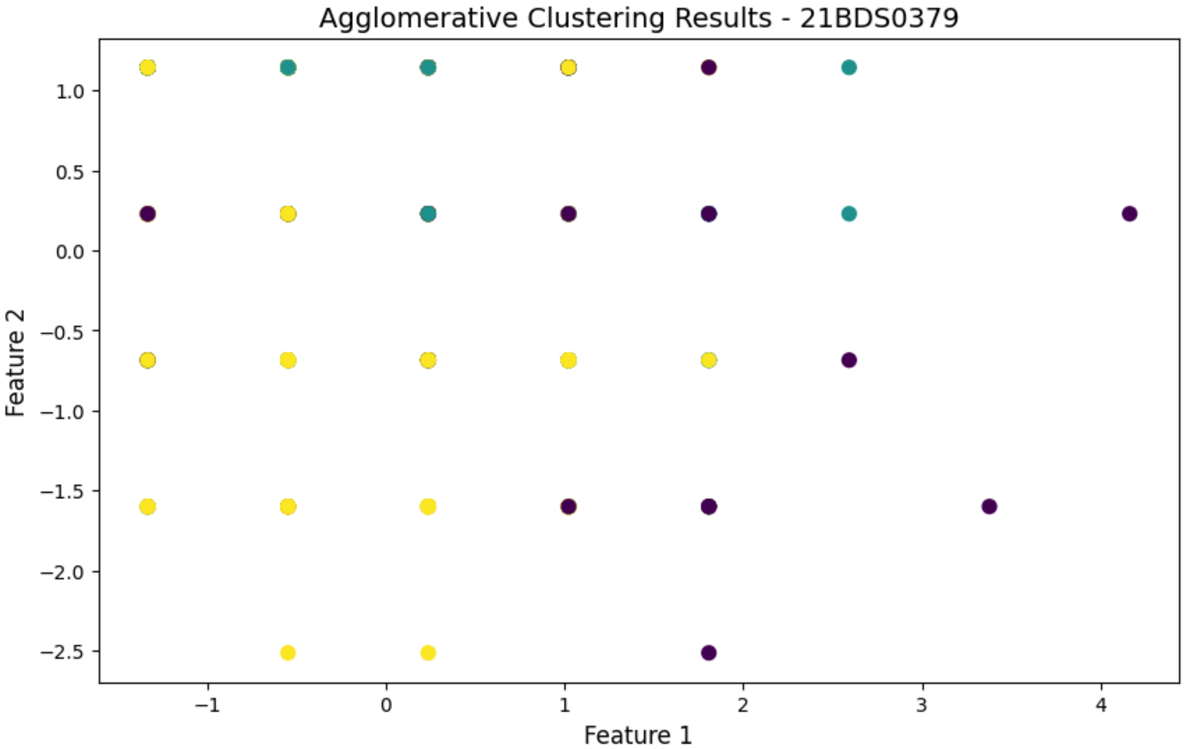


In [40]:

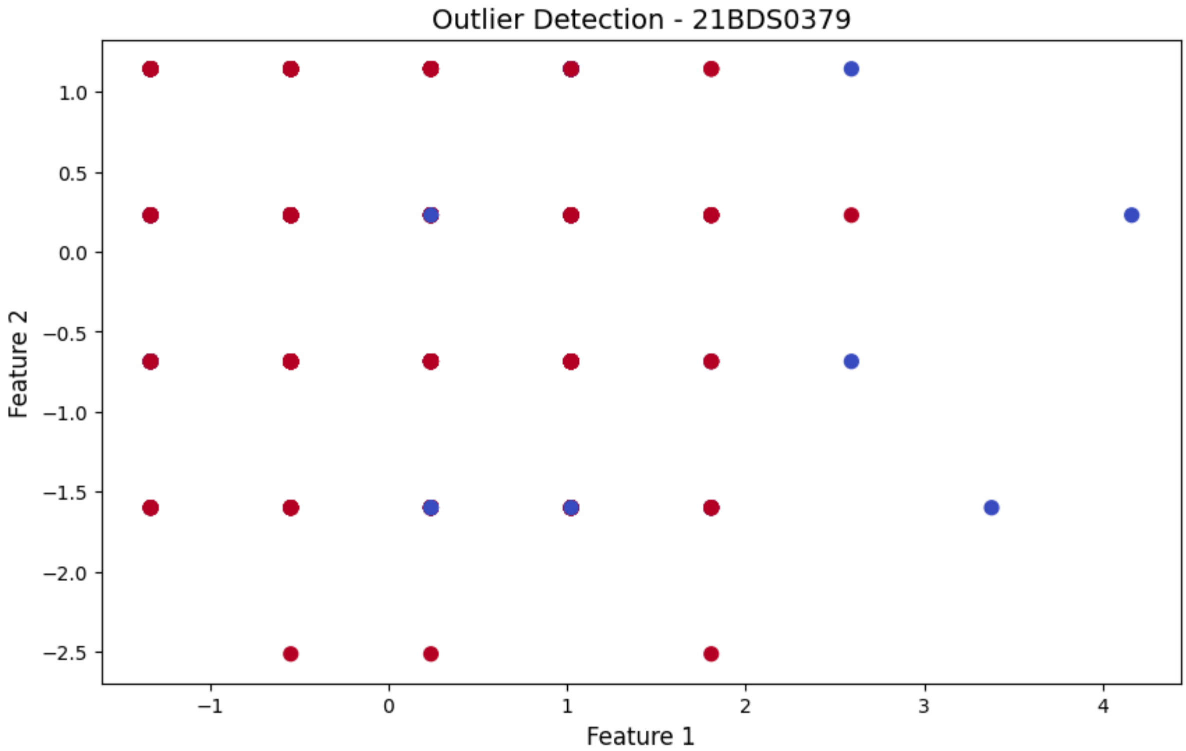
```
# Model-based Clustering using Expectation-Maximization (Gaussian Mixture Model)
gmm = GaussianMixture(n_components=3, random_state=42)
labels_gmm = gmm.fit_predict(scaled_data)

# Plot GMM Clustering Results
plt.figure(figsize=(10, 6))
plt.scatter(scaled_data[:, 0], scaled_data[:, 1], c=labels_gmm, cmap='viridis', s=50)
plt.title("GMM Clustering Results - 21BDS0379", fontsize=14)
plt.xlabel("Feature 1", fontsize=12)
plt.ylabel("Feature 2", fontsize=12)
plt.show()
```



In [41]:
```python
# Hierarchical Agglomerative Clustering
agg_clust = AgglomerativeClustering(n_clusters=3)
labels_agg = agg_clust.fit_predict(scaled_data)

# Plot Hierarchical Agglomerative Clustering Results
plt.figure(figsize=(10, 6))
plt.scatter(scaled_data[:, 0], scaled_data[:, 1], c=labels_agg, cmap='viridis', s=50)
plt.title("Agglomerative Clustering Results - 21BDS0379", fontsize=14)
plt.xlabel("Feature 1", fontsize=12)
plt.ylabel("Feature 2", fontsize=12)
plt.show()
```

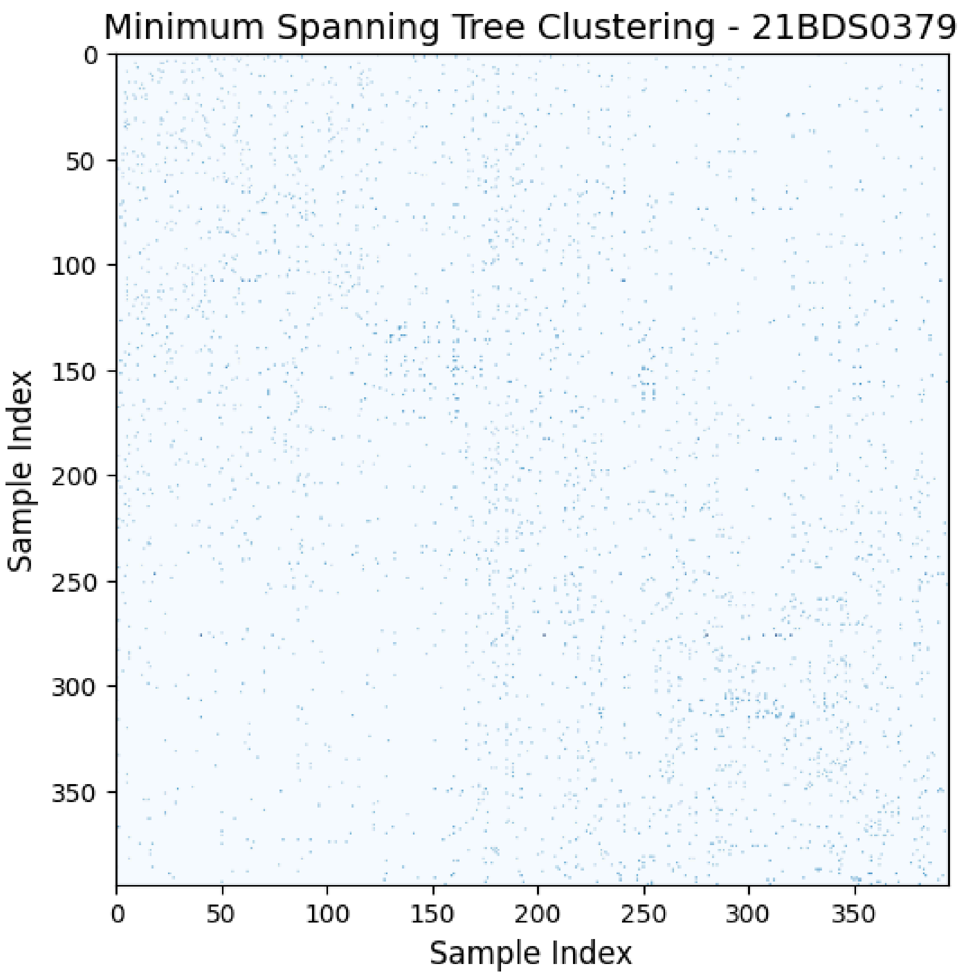


In [42]:
```python
# Outlier Detection using Isolation Forest
from sklearn.ensemble import IsolationForest

iso_forest = IsolationForest(contamination=0.1, random_state=42)
outliers = iso_forest.fit_predict(scaled_data)

# Plotting the Outliers
plt.figure(figsize=(10, 6))
plt.scatter(scaled_data[:, 0], scaled_data[:, 1], c=outliers, cmap='coolwarm', s=50)
plt.title("Outlier Detection - 21BDS0379", fontsize=14)
plt.xlabel("Feature 1", fontsize=12)
plt.ylabel("Feature 2", fontsize=12)
plt.show()
```



In [43]:

```
# Minimum Spanning Tree (MST) for Clustering
distance_matrix = pdist(scaled_data)
square_dist = squareform(distance_matrix)
graph = kneighbors_graph(scaled_data, n_neighbors=10, mode='distance', include_self=True)

# Plot MST
plt.figure(figsize=(10, 6))
plt.imshow(graph.toarray(), cmap='Blues')
plt.title("Minimum Spanning Tree Clustering - 21BDS0379", fontsize=14)
plt.xlabel("Sample Index", fontsize=12)
plt.ylabel("Sample Index", fontsize=12)
plt.show()
```



In [44]:
```
# Evaluate Clustering using Silhouette Score (for GMM as an example)
silhouette_avg = silhouette_score(scaled_data, labels_gmm)
print(f"Silhouette Score for GMM Clustering: {silhouette_avg}")
```

```
Silhouette Score for GMM Clustering: 0.1394450326877308
```

Module 6

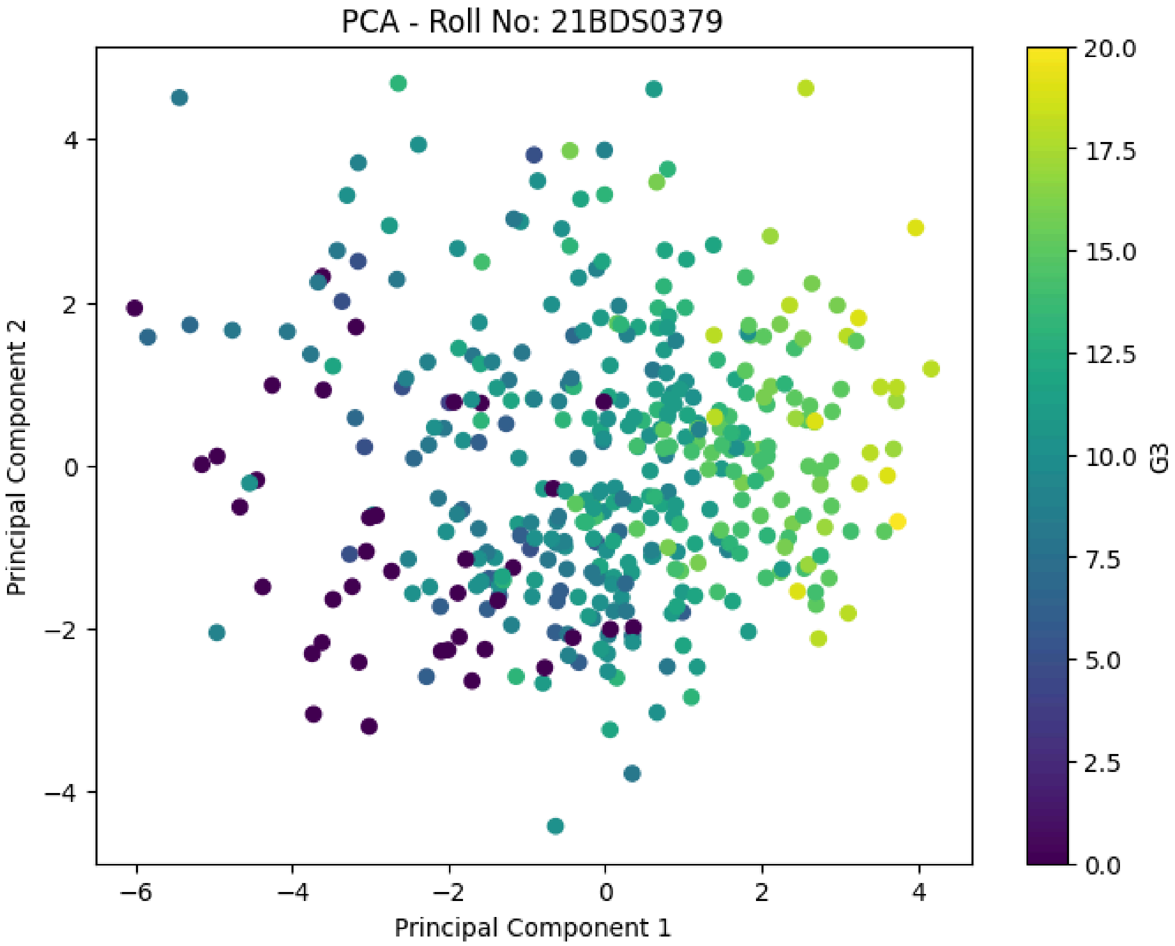
In [48]:
```
# Required Libraries
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA, TruncatedSVD
from sklearn.manifold import MDS, Isomap
from sklearn.preprocessing import StandardScaler
#from sklearn.factor_analysis import FactorAnalysis #This was removed in recent versions
from factor_analyzer import FactorAnalyzer #Use this instead
from sklearn import datasets
from sklearn.preprocessing import LabelEncoder
from minisom import MiniSom
import pandas as pd # Import pandas
```

In [49]:
```
# Load the dataset  (Assuming your dataset is in 'MyDataset_EDA.csv')
dataset = pd.read_csv('MyDataset_EDA.csv') # Load the dataset into 'dataset'

# Encoding categorical columns
dataset_encoded = dataset.copy()

# Encoding categorical features (like 'sex', 'address', 'famsize', etc.)
label_columns = ['school', 'sex', 'address', 'famsize', 'Pstatus', 'Mjob', 'Fjob', 'reason'

label_encoder = LabelEncoder()

for col in label_columns:
```

```
    dataset_encoded[col] = label_encoder.fit_transform(dataset_encoded[col])

# Extract numerical features (excluding the categorical features and target columns)
numerical_features = dataset_encoded.select_dtypes(include=[np.number])

# Standardizing the features (important for methods like PCA, SVD)
scaler = StandardScaler()
numerical_features_scaled = scaler.fit_transform(numerical_features)

# Roll number (for titles)
roll_no = "21BDS0379"
```

In [50]:

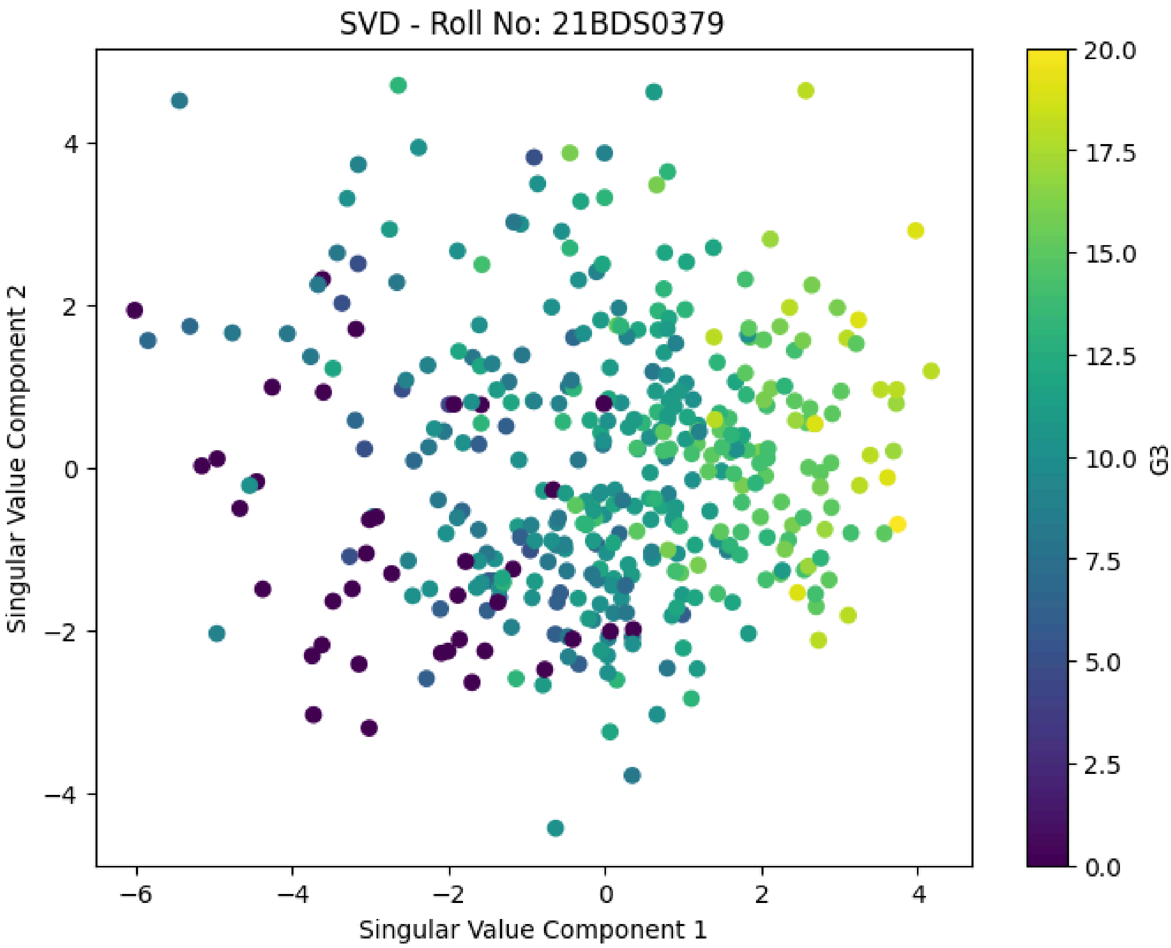
```
# 1. Principal Component Analysis (PCA)
pca = PCA(n_components=2)
pca_result = pca.fit_transform(numerical_features_scaled)

plt.figure(figsize=(8, 6))
plt.scatter(pca_result[:, 0], pca_result[:, 1], c=dataset_encoded['G3'], cmap='viridis')
plt.title(f"PCA - Roll No: {roll_no}")
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar(label='G3')
plt.show()
```



In [51]:

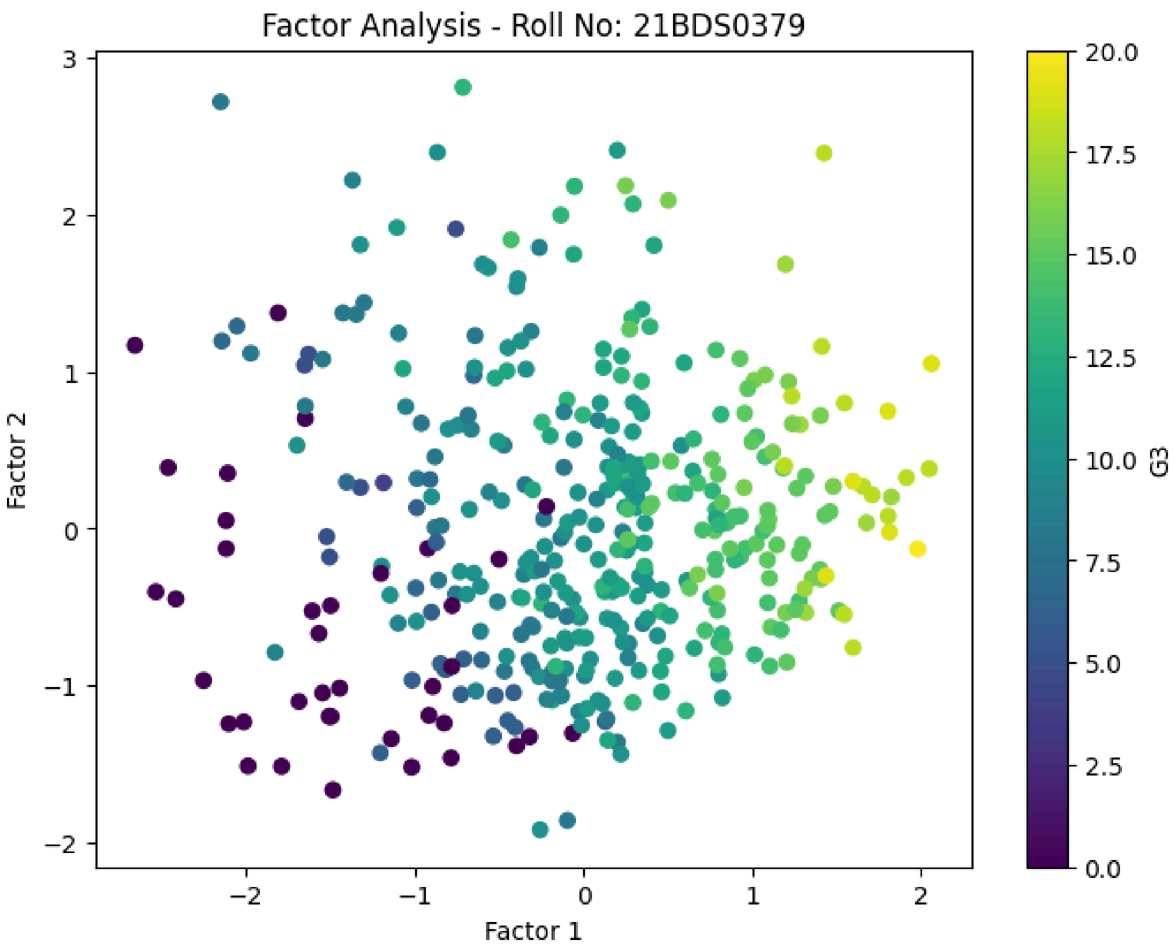
```
# 2. Singular Value Decomposition (SVD)
svd = TruncatedSVD(n_components=2)
svd_result = svd.fit_transform(numerical_features_scaled)

plt.figure(figsize=(8, 6))
plt.scatter(svd_result[:, 0], svd_result[:, 1], c=dataset_encoded['G3'], cmap='viridis')
plt.title(f"SVD - Roll No: {roll_no}")
plt.xlabel('Singular Value Component 1')
plt.ylabel('Singular Value Component 2')
```

```
plt.colorbar(label='G3')
plt.show()
```



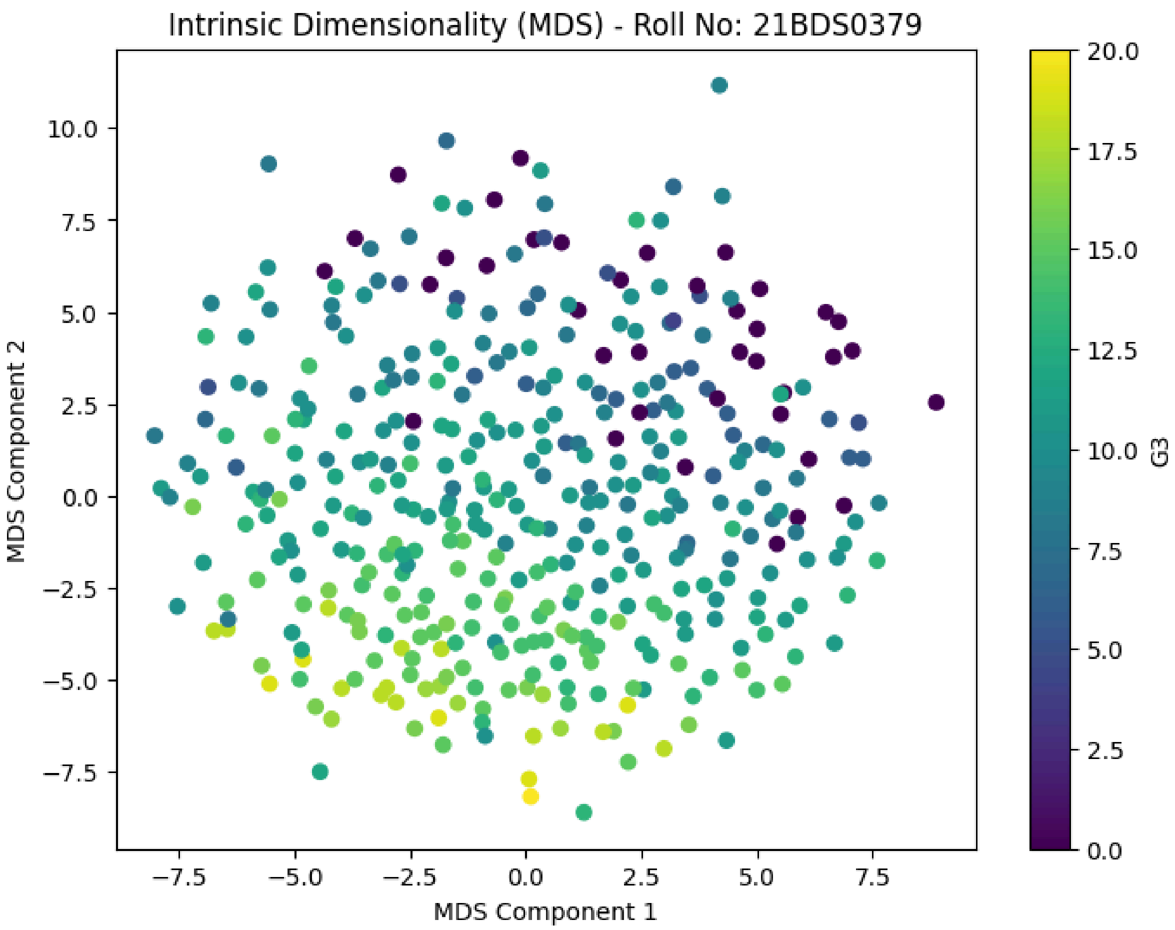
In [52]:

```
# 3. Factor Analysis
factor = FactorAnalyzer(n_factors=2, rotation=None) #Updated to use FactorAnalyzer
factor_result = factor.fit_transform(numerical_features_scaled)

plt.figure(figsize=(8, 6))
plt.scatter(factor_result[:, 0], factor_result[:, 1], c=dataset_encoded['G3'], cmap='viridi
plt.title(f"Factor Analysis - Roll No: {roll_no}")
plt.xlabel('Factor 1')
plt.ylabel('Factor 2')
plt.colorbar(label='G3')
plt.show()
```

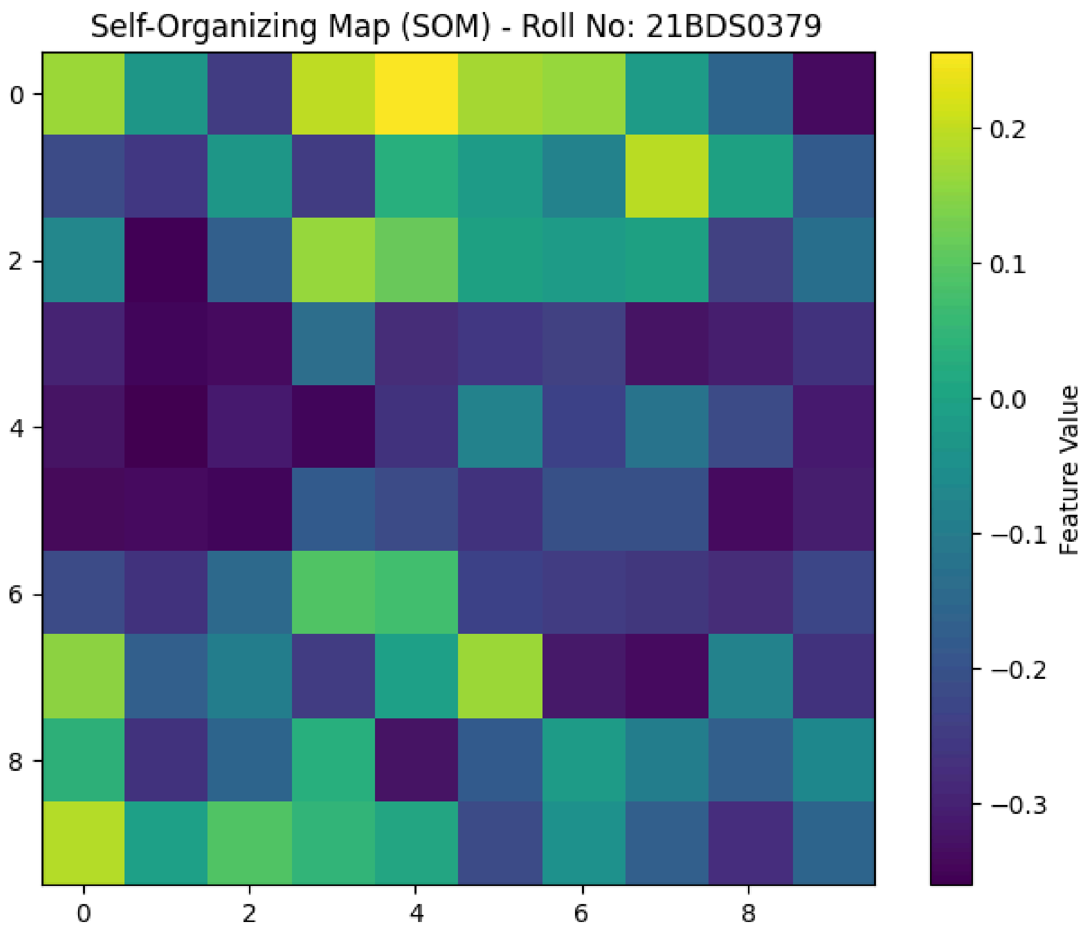


In [53]:

```
# 4. Intrinsic Dimensionality (Using MDS to estimate intrinsic dimensionality)
mds = MDS(n_components=2)
mds_result = mds.fit_transform(numerical_features_scaled)

plt.figure(figsize=(8, 6))
plt.scatter(mds_result[:, 0], mds_result[:, 1], c=dataset_encoded['G3'], cmap='viridis')
plt.title(f"Intrinsic Dimensionality (MDS) - Roll No: {roll_no}")
plt.xlabel('MDS Component 1')
plt.ylabel('MDS Component 2')
plt.colorbar(label='G3')
plt.show()
```



In [54]:
```
# 5. Self-Organizing Maps (SOM)
som = MiniSom(x=10, y=10, input_len=numerical_features_scaled.shape[1], sigma=1.0, learning
som.train(numerical_features_scaled, 100)

# Getting the weights for each node in the SOM
som_result = som.get_weights()

# Visualizing the SOM grid
plt.figure(figsize=(8, 6))
plt.imshow(som_result[:, :, 0], cmap='viridis')  # Visualizing the first feature
plt.title(f"Self-Organizing Map (SOM) - Roll No: {roll_no}")
plt.colorbar(label='Feature Value')
plt.show()
```



Module 7

In [55]:
```
# Import necessary libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import matplotlib.pyplot as plt
```

In [56]:
```
# Load the dataset
data = pd.read_csv('MyDataset_EDA.csv')

# Preprocess data: Convert categorical variables to numeric using get_dummies
data_processed = pd.get_dummies(data, drop_first=True)

# Define features (X) and target (y)
X = data_processed.drop(columns=['G3'])
y = data_processed['G3']

# Split the data into training and test sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=379)
```

In [57]:
```
# Initialize and train the linear regression model
model = LinearRegression()
model.fit(X_train, y_train)
```

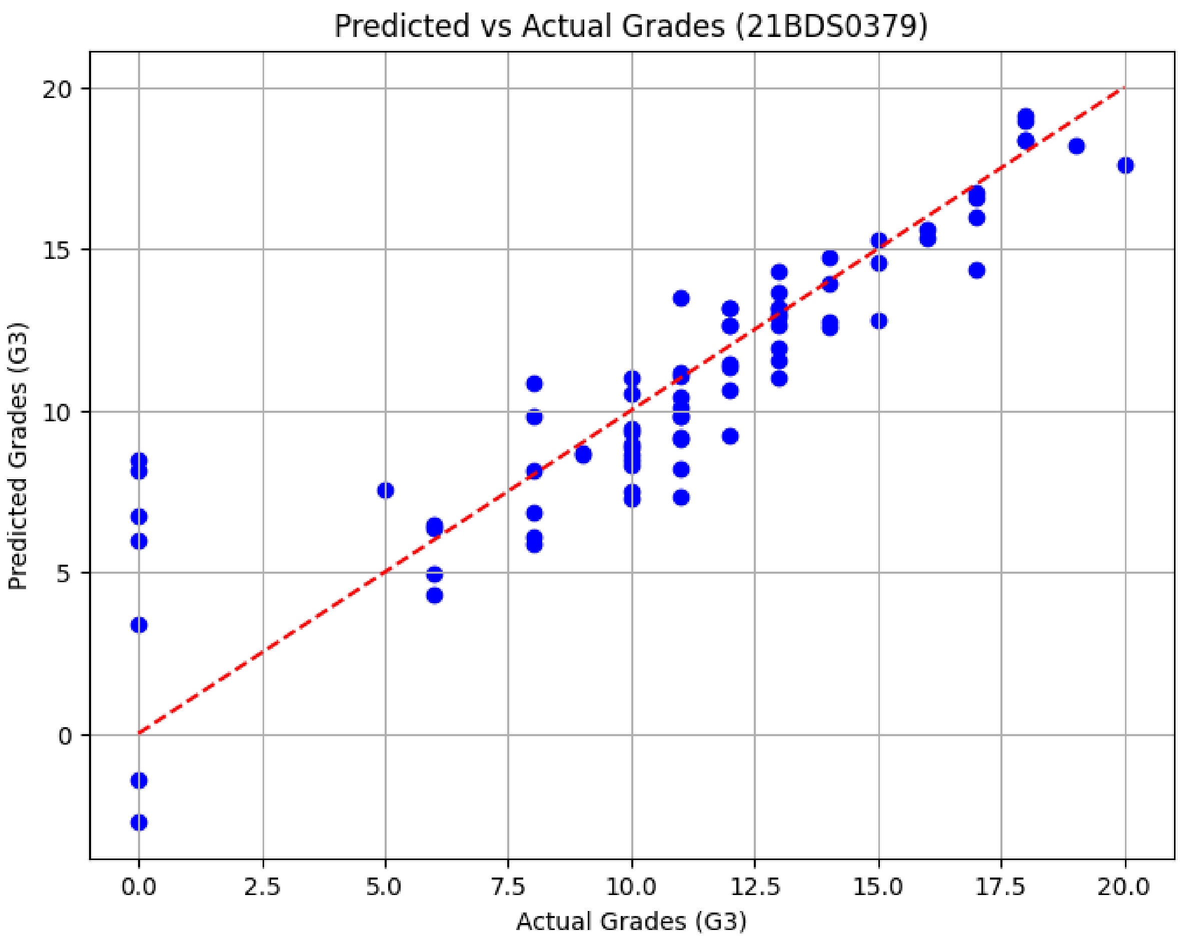
Out[57]:
```
▾ LinearRegression
LinearRegression()
```

In [58]:

```
# Make predictions on the test set
y_pred = model.predict(X_test)
```

In [59]:

```
# Plotting predicted vs actual grades
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linestyle='--
plt.title(f"Predicted vs Actual Grades (21BDS0379)")
plt.xlabel("Actual Grades (G3)")
plt.ylabel("Predicted Grades (G3)")
plt.grid(True)
plt.show()
```



In [60]:

```
# Evaluate the model
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = mse ** 0.5
r2 = r2_score(y_test, y_pred)
```

In [61]:

```
# Display evaluation metrics
evaluation_metrics = {
    'Mean Absolute Error (MAE)': mae,
    'Mean Squared Error (MSE)': mse,
    'Root Mean Squared Error (RMSE)': rmse,
    'R-Squared (R2)': r2
}

print("Model Evaluation Metrics:")
for metric, value in evaluation_metrics.items():
    print(f"{metric}: {value}")
```

```
Model Evaluation Metrics:
Mean Absolute Error (MAE): 1.511114416734068
Mean Squared Error (MSE): 4.8923133684557065
Root Mean Squared Error (RMSE): 2.2118574475891766
R-Squared (R2): 0.7756449480312431
```