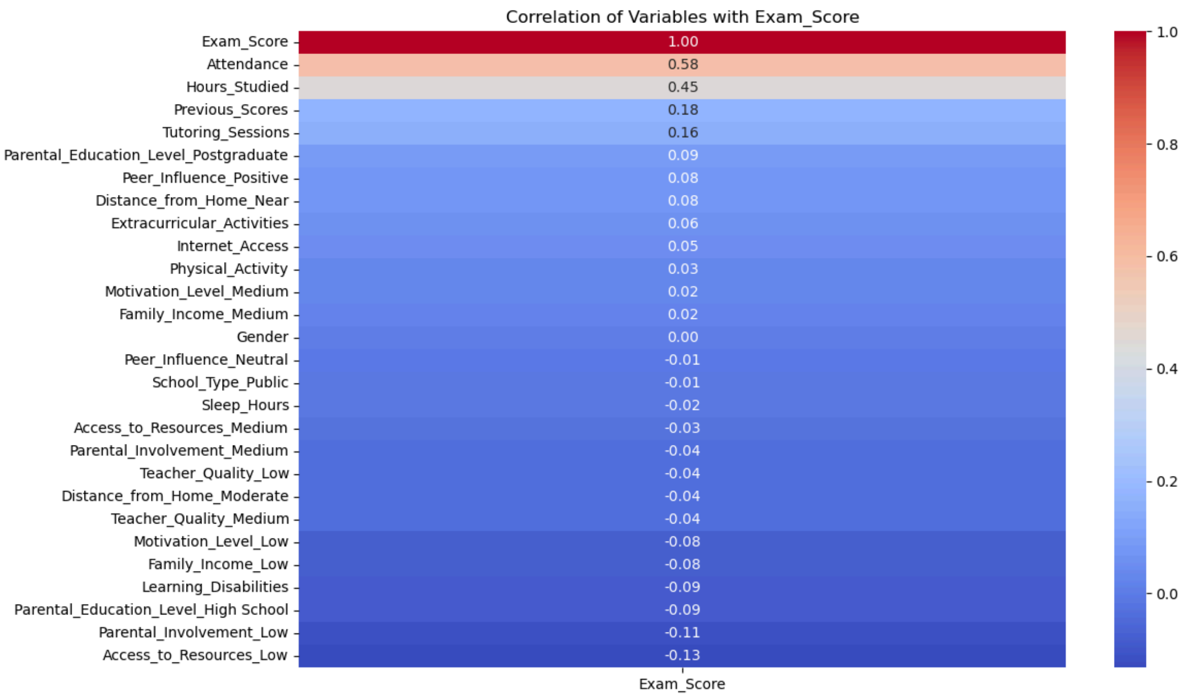
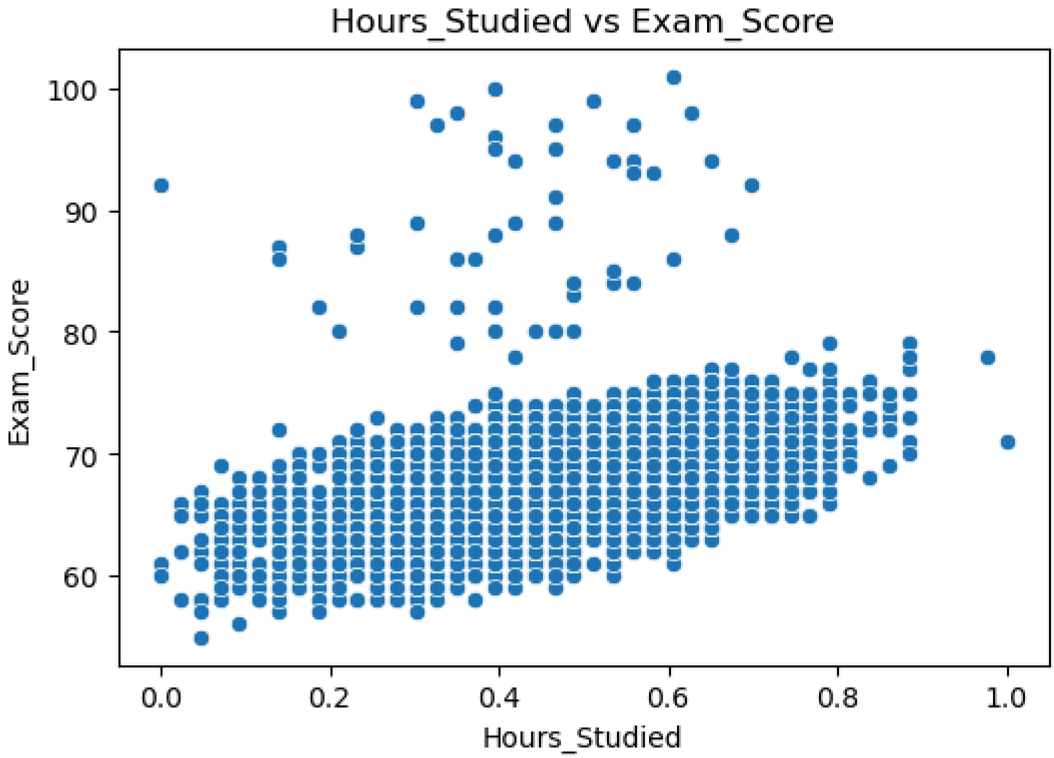
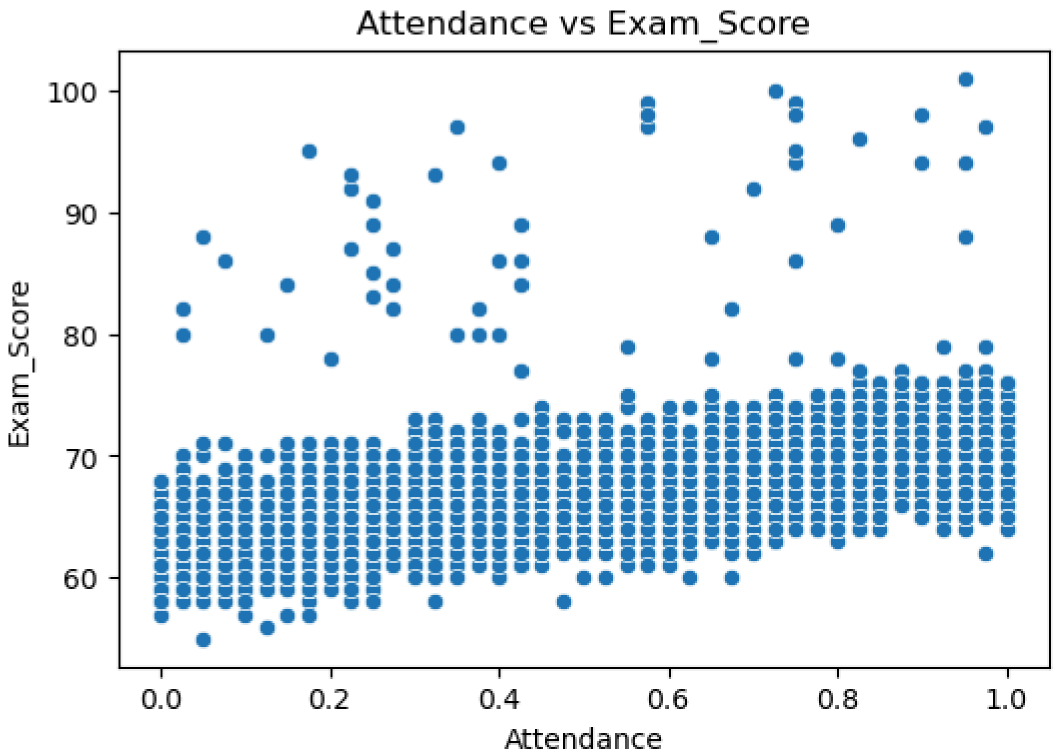
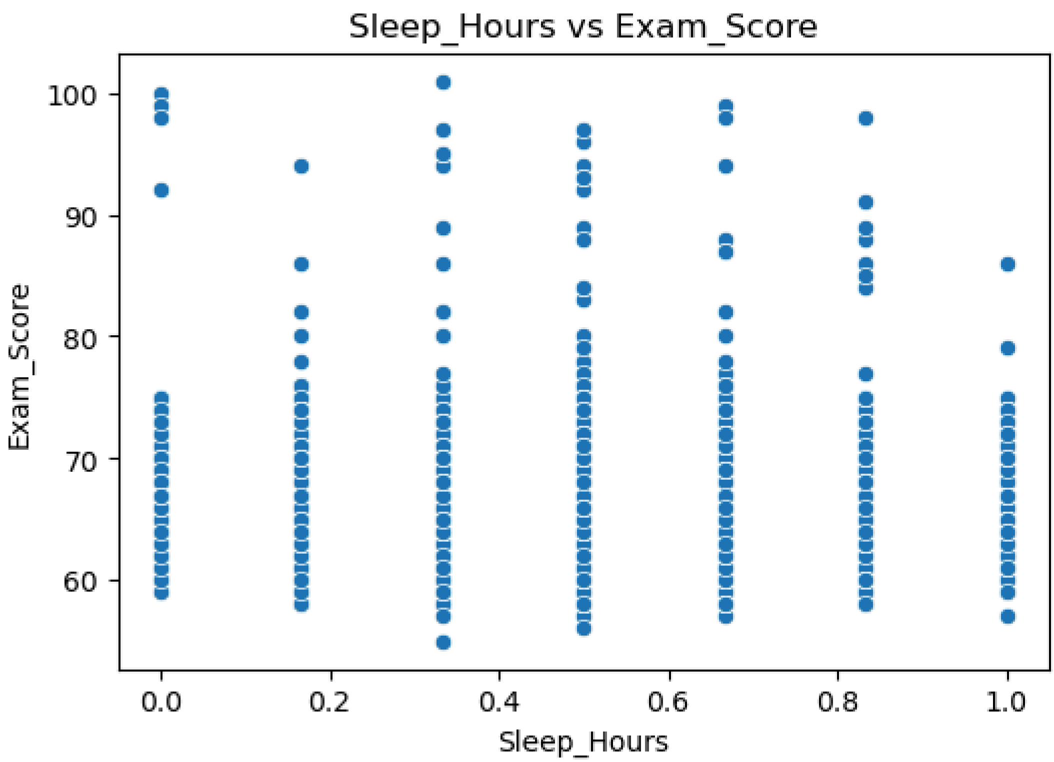
In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score


data = pd.read_csv('StudentPerformanceFactors.csv')

# Step 1: Data Cleaning
# Impute missing values with mode for categorical columns
categorical_cols_with_missing = ['Teacher_Quality', 'Parental_Education_Level', 'Dis
for col in categorical_cols_with_missing:
    data[col].fillna(data[col].mode()[0], inplace=True)

# Step 2: Encode Categorical Variables
# Use one-hot encoding for variables with more than two categories
data_encoded = pd.get_dummies(data, columns=[
    'Parental_Involvement', 'Access_to_Resources', 'Motivation_Level',
    'Family_Income', 'Teacher_Quality', 'School_Type', 'Peer_Influence',
    'Parental_Education_Level', 'Distance_from_Home'
], drop_first=True)

# Label encode binary variables
binary_mappings = {
    'Extracurricular_Activities': {'No': 0, 'Yes': 1},
    'Internet_Access': {'No': 0, 'Yes': 1},
    'Learning_Disabilities': {'No': 0, 'Yes': 1},
    'Gender': {'Male': 0, 'Female': 1}
}
data_encoded.replace(binary_mappings, inplace=True)

# Normalize numerical variables for consistency
scaler = MinMaxScaler()
numerical_cols = ['Hours_Studied', 'Attendance', 'Sleep_Hours',
                  'Previous_Scores', 'Tutoring_Sessions', 'Physical_Activity']
data_encoded[numerical_cols] = scaler.fit_transform(data_encoded[numerical_cols])

# Step 3: Exploratory Data Analysis
# Correlation heatmap
correlation_matrix = data_encoded.corr()
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix[['Exam_Score']].sort_values(by='Exam_Score', ascendin
            annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation of Variables with Exam_Score')
plt.show()

# Scatter plots for numerical features
for col in numerical_cols:
    plt.figure(figsize=(6, 4))
    sns.scatterplot(x=data_encoded[col], y=data_encoded['Exam_Score'])
    plt.title(f'{col} vs Exam_Score')
    plt.xlabel(col)
    plt.ylabel('Exam_Score')
    plt.show()

# Boxplots for binary features
binary_features = ['Extracurricular_Activities', 'Internet_Access', 'Learning_Disabi
for col in binary_features:
```

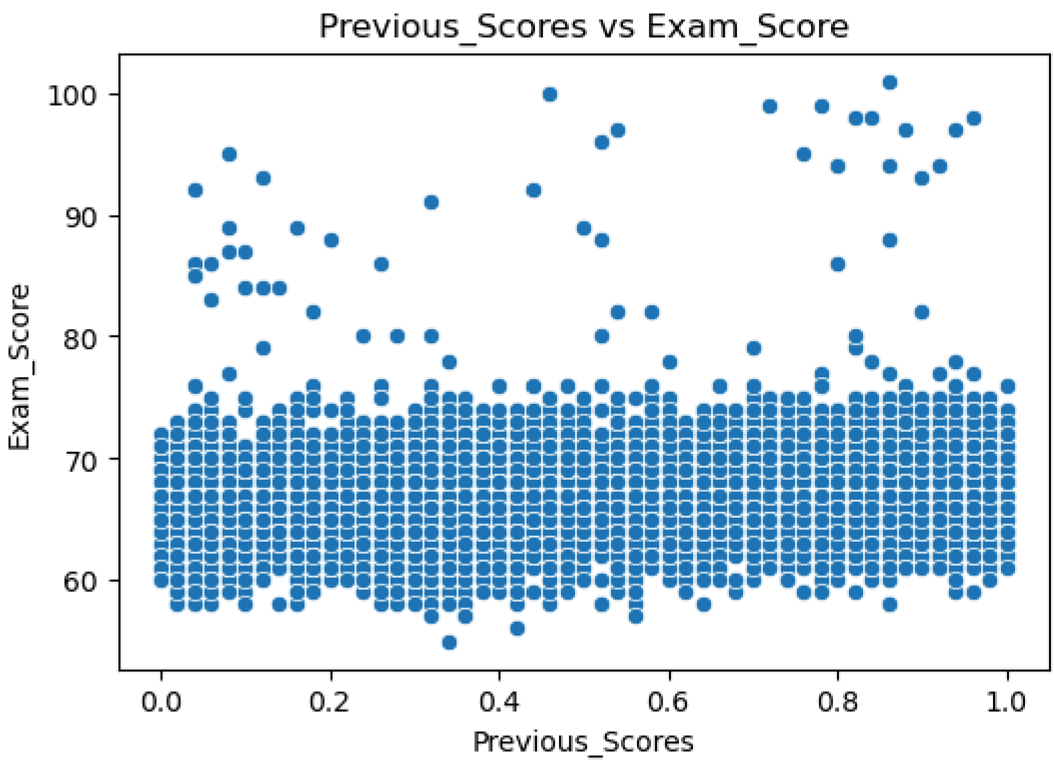
```
    plt.figure(figsize=(6, 4))
    sns.boxplot(x=data_encoded[col], y=data_encoded['Exam_Score'])
    plt.title(f'{col} vs Exam_Score')
    plt.xlabel(col)
    plt.ylabel('Exam_Score')
    plt.show()

# Step 4: Analyze Influence of Variables
# Split data into features and target
X = data_encoded.drop(columns=['Exam_Score'])
y = data_encoded['Exam_Score']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_stat

# Train a Random Forest Regressor
rf_model = RandomForestRegressor(random_state=42, n_estimators=100)
rf_model.fit(X_train, y_train)

# Feature importance
feature_importances = pd.DataFrame({
    'Feature': X.columns,
    'Importance': rf_model.feature_importances_
}).sort_values(by='Importance', ascending=False)

# Display feature importances
print("Feature Importance Analysis:")
print(feature_importances)

# Evaluate model performance
y_pred = rf_model.predict(X_test)
model_performance = r2_score(y_test, y_pred)
print(f"\nModel R^2 Score: {model_performance:.3f}")
```

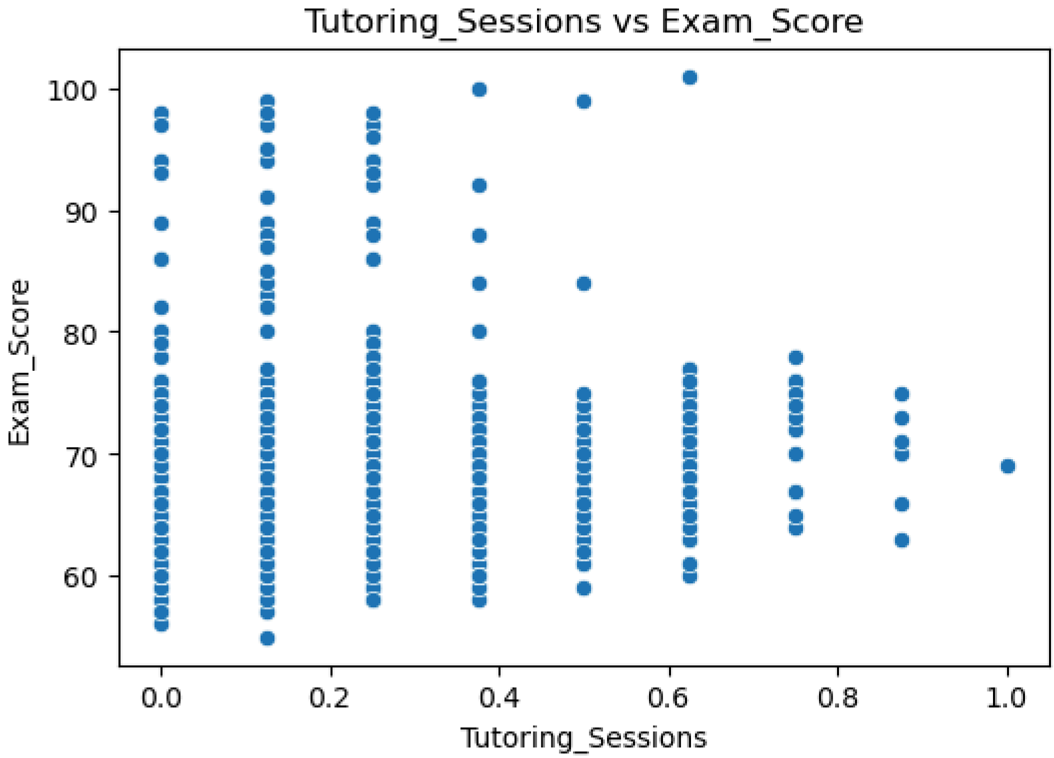


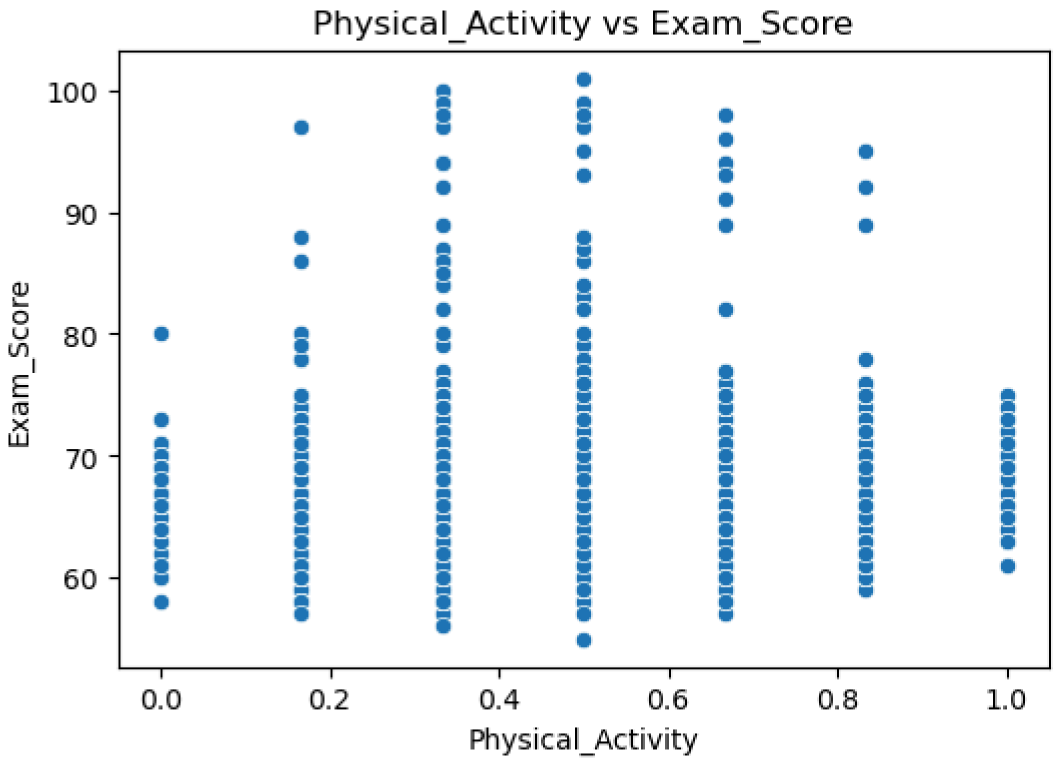

Hours_Studied vs Exam_Score
Exam_Score
Hours_Studied
100
90
80
70
60
0.0
0.2
0.4
0.6
0.8
1.0

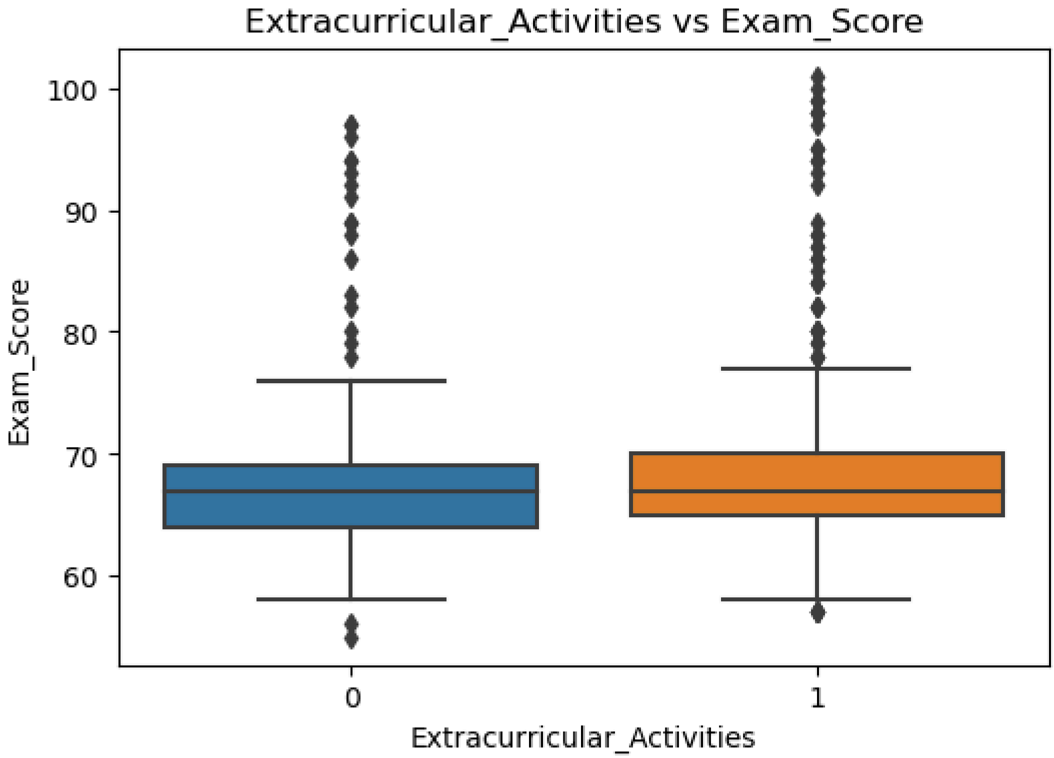

Attendance vs Exam_Score
Exam_Score
Attendance
100
90
80
70
60
0.0
0.2
0.4
0.6
0.8
1.0

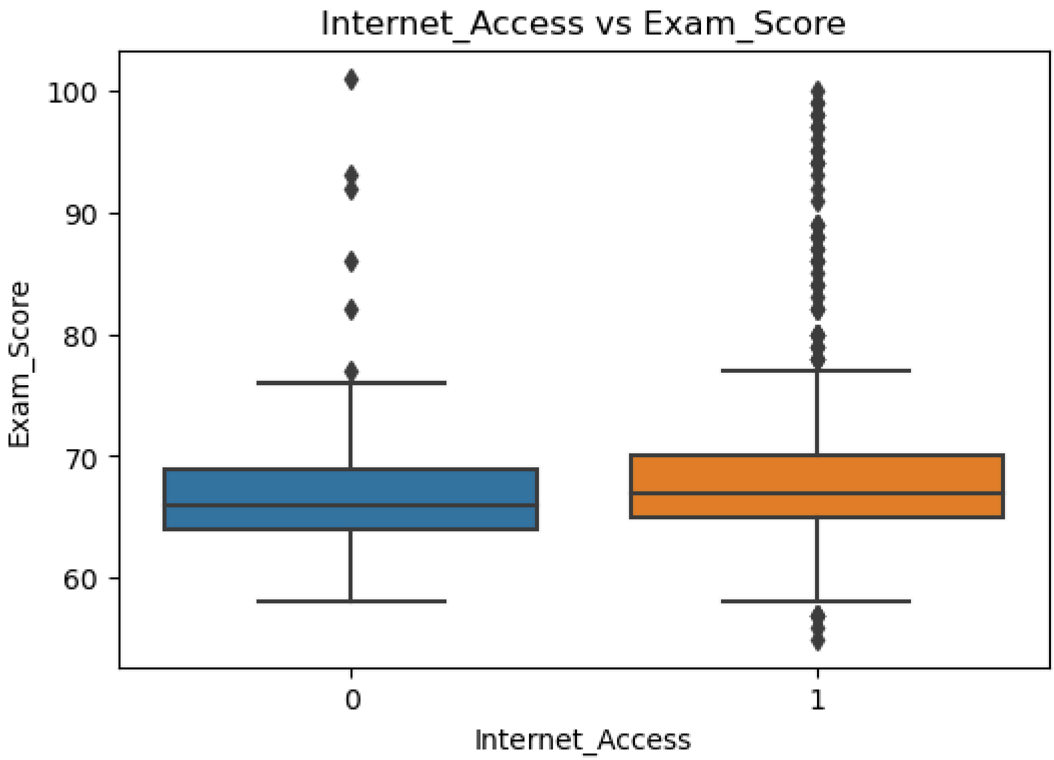

Sleep_Hours vs Exam_Score
Exam_Score
100
90
80
70
60
0.0
0.2
0.4
0.6
0.8
1.0
Sleep_Hours

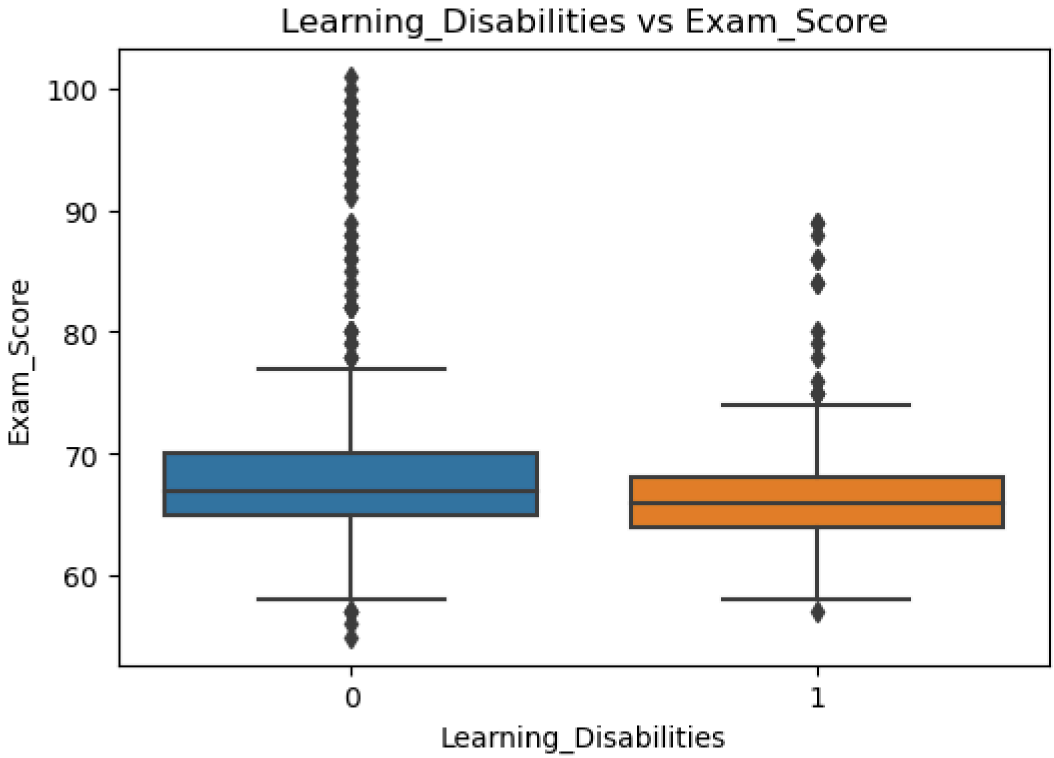

Previous_Scores vs Exam_Score
Exam_Score
100
90
80
70
60
0.0
0.2
0.4
0.6
0.8
1.0
Previous_Scores

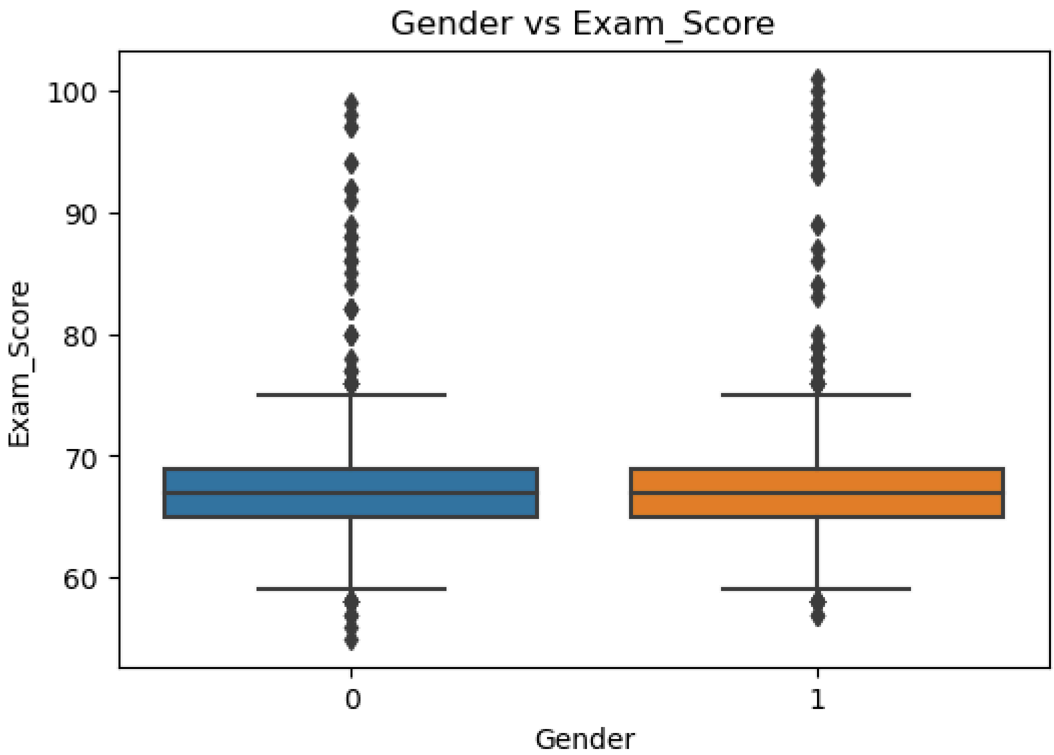

Tutoring_Sessions vs Exam_Score
Exam_Score
100
90
80
70
60
0.0
0.2
0.4
0.6
0.8
1.0
Tutoring_Sessions


Physical_Activity vs Exam_Score
Exam_Score
100
90
80
70
60
0.0
0.2
0.4
0.6
0.8
1.0
Physical_Activity


Extracurricular_Activities vs Exam_Score
Exam_Score
100
90
80
70
60
0
1
Extracurricular_Activities


Internet_Access vs Exam_Score
Exam_Score
100
90
80
70
60
0
1
Internet_Access


Learning_Disabilities vs Exam_Score
Exam_Score
100
90
80
70
60
0
1
Learning_Disabilities


Gender vs Exam_Score
Exam_Score
100
90
80
70
60
0
1
Gender

```
Feature Importance Analysis:
                                   Feature  Importance
1                               Attendance    0.382619
0                            Hours_Studied    0.240712
4                          Previous_Scores    0.090990
6                        Tutoring_Sessions    0.037418
7                        Physical_Activity    0.027355
3                              Sleep_Hours    0.026713
10                 Parental_Involvement_Low    0.020549
12                  Access_to_Resources_Low    0.017614
13               Access_to_Resources_Medium    0.012028
24   Parental_Education_Level_Postgraduate    0.010898
8                    Learning_Disabilities    0.010165
22                  Peer_Influence_Positive    0.010121
11              Parental_Involvement_Medium    0.009611
2                Extracurricular_Activities    0.009417
16                       Family_Income_Low    0.008891
26                  Distance_from_Home_Near    0.008851
19                   Teacher_Quality_Medium    0.008737
23    Parental_Education_Level_High School    0.008477
14                    Motivation_Level_Low    0.008246
20                      School_Type_Public    0.008133
9                                   Gender    0.007179
21                   Peer_Influence_Neutral    0.007108
17                    Family_Income_Medium    0.006695
25             Distance_from_Home_Moderate    0.005767
5                          Internet_Access    0.005472
15                 Motivation_Level_Medium    0.005149
18                     Teacher_Quality_Low    0.005084

Model R^2 Score: 0.649
```

In [5]:

```
pip install causalgraphicalmodels
```

```
Collecting causalgraphicalmodels
  Downloading causalgraphicalmodels-0.0.4-py3-none-any.whl (11 kB)
Requirement already satisfied: networkx in d:\jupyter\lib\site-packages (from causal
graphicalmodels) (2.8.4)
Requirement already satisfied: numpy in d:\jupyter\lib\site-packages (from causalgra
phicalmodels) (1.23.5)
Requirement already satisfied: pandas in d:\jupyter\lib\site-packages (from causalgr
aphicalmodels) (1.5.3)
Collecting graphviz
  Downloading graphviz-0.20.3-py3-none-any.whl (47 kB)
     -------------------------------------- 47.1/47.1 kB 131.3 kB/s eta 0:00:00
Requirement already satisfied: python-dateutil>=2.8.1 in d:\jupyter\lib\site-package
s (from pandas->causalgraphicalmodels) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in d:\jupyter\lib\site-packages (from pa
ndas->causalgraphicalmodels) (2022.7)
Requirement already satisfied: six>=1.5 in d:\jupyter\lib\site-packages (from python
-dateutil>=2.8.1->pandas->causalgraphicalmodels) (1.16.0)
Installing collected packages: graphviz, causalgraphicalmodels
Successfully installed causalgraphicalmodels-0.0.4 graphviz-0.20.3
Note: you may need to restart the kernel to use updated packages.
```

In [7]:

```
pip install dowhy
```

```
Collecting dowhy
  Downloading dowhy-0.11.1-py3-none-any.whl (383 kB)
     ------------------------------------ 383.4/383.4 kB 341.4 kB/s eta 0:00:00
Requirement already satisfied: joblib>=1.1.0 in d:\jupyter\lib\site-packages (from d
owhy) (1.1.1)
Requirement already satisfied: cvxpy<2.0.0,>=1.2.2 in d:\jupyter\lib\site-packages
(from dowhy) (1.5.3)
Collecting cython>=0.29.32
  Downloading Cython-3.0.11-cp310-cp310-win_amd64.whl (2.8 MB)
     ---------------------------------------- 2.8/2.8 MB 946.7 kB/s eta 0:00:00
Requirement already satisfied: sympy>=1.10.1 in d:\jupyter\lib\site-packages (from d
owhy) (1.11.1)
Collecting networkx>=2.8.5
  Downloading networkx-3.4.2-py3-none-any.whl (1.7 MB)
     ---------------------------------------- 1.7/1.7 MB 921.0 kB/s eta 0:00:00
Requirement already satisfied: statsmodels>=0.13.5 in d:\jupyter\lib\site-packages
(from dowhy) (0.13.5)
Requirement already satisfied: pandas>=1.4.3 in d:\jupyter\lib\site-packages (from d
owhy) (1.5.3)
Requirement already satisfied: tqdm>=4.64.0 in d:\jupyter\lib\site-packages (from do
why) (4.64.1)
Collecting causal-learn>=0.1.3.0
  Downloading causal_learn-0.1.3.8-py3-none-any.whl (174 kB)
     -------------------------------------- 174.5/174.5 kB 2.6 MB/s eta 0:00:00
Requirement already satisfied: numpy>=1.20 in d:\jupyter\lib\site-packages (from dow
hy) (1.23.5)
Requirement already satisfied: scipy>=1.4.1 in d:\jupyter\lib\site-packages (from do
why) (1.10.0)
Requirement already satisfied: scikit-learn>1.0 in d:\jupyter\lib\site-packages (fro
m dowhy) (1.2.1)
Requirement already satisfied: graphviz in d:\jupyter\lib\site-packages (from causal
-learn>=0.1.3.0->dowhy) (0.20.3)
Collecting pydot
  Downloading pydot-3.0.2-py3-none-any.whl (35 kB)
Requirement already satisfied: matplotlib in d:\jupyter\lib\site-packages (from caus
al-learn>=0.1.3.0->dowhy) (3.7.0)
Requirement already satisfied: clarabel>=0.5.0 in d:\jupyter\lib\site-packages (from
cvxpy<2.0.0,>=1.2.2->dowhy) (0.9.0)
Requirement already satisfied: osqp>=0.6.2 in d:\jupyter\lib\site-packages (from cvx
py<2.0.0,>=1.2.2->dowhy) (0.6.7.post1)
Requirement already satisfied: scs>=3.2.4.post1 in d:\jupyter\lib\site-packages (fro
m cvxpy<2.0.0,>=1.2.2->dowhy) (3.2.7)
Requirement already satisfied: ecos>=2 in d:\jupyter\lib\site-packages (from cvxpy<
2.0.0,>=1.2.2->dowhy) (2.0.14)
Requirement already satisfied: pytz>=2020.1 in d:\jupyter\lib\site-packages (from pa
ndas>=1.4.3->dowhy) (2022.7)
Requirement already satisfied: python-dateutil>=2.8.1 in d:\jupyter\lib\site-package
s (from pandas>=1.4.3->dowhy) (2.8.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in d:\jupyter\lib\site-packages
(from scikit-learn>1.0->dowhy) (2.2.0)
Requirement already satisfied: packaging>=21.3 in d:\jupyter\lib\site-packages (from
statsmodels>=0.13.5->dowhy) (22.0)
Requirement already satisfied: patsy>=0.5.2 in d:\jupyter\lib\site-packages (from st
atsmodels>=0.13.5->dowhy) (0.5.3)
Requirement already satisfied: mpmath>=0.19 in d:\jupyter\lib\site-packages (from sy
mpy>=1.10.1->dowhy) (1.2.1)
Requirement already satisfied: colorama in d:\jupyter\lib\site-packages (from tqdm>=
4.64.0->dowhy) (0.4.6)
Requirement already satisfied: qdldl in d:\jupyter\lib\site-packages (from osqp>=0.
6.2->cvxpy<2.0.0,>=1.2.2->dowhy) (0.1.7.post4)
Requirement already satisfied: six in d:\jupyter\lib\site-packages (from patsy>=0.5.
2->statsmodels>=0.13.5->dowhy) (1.16.0)
Requirement already satisfied: contourpy>=1.0.1 in d:\jupyter\lib\site-packages (fro
m matplotlib->causal-learn>=0.1.3.0->dowhy) (1.0.5)
```

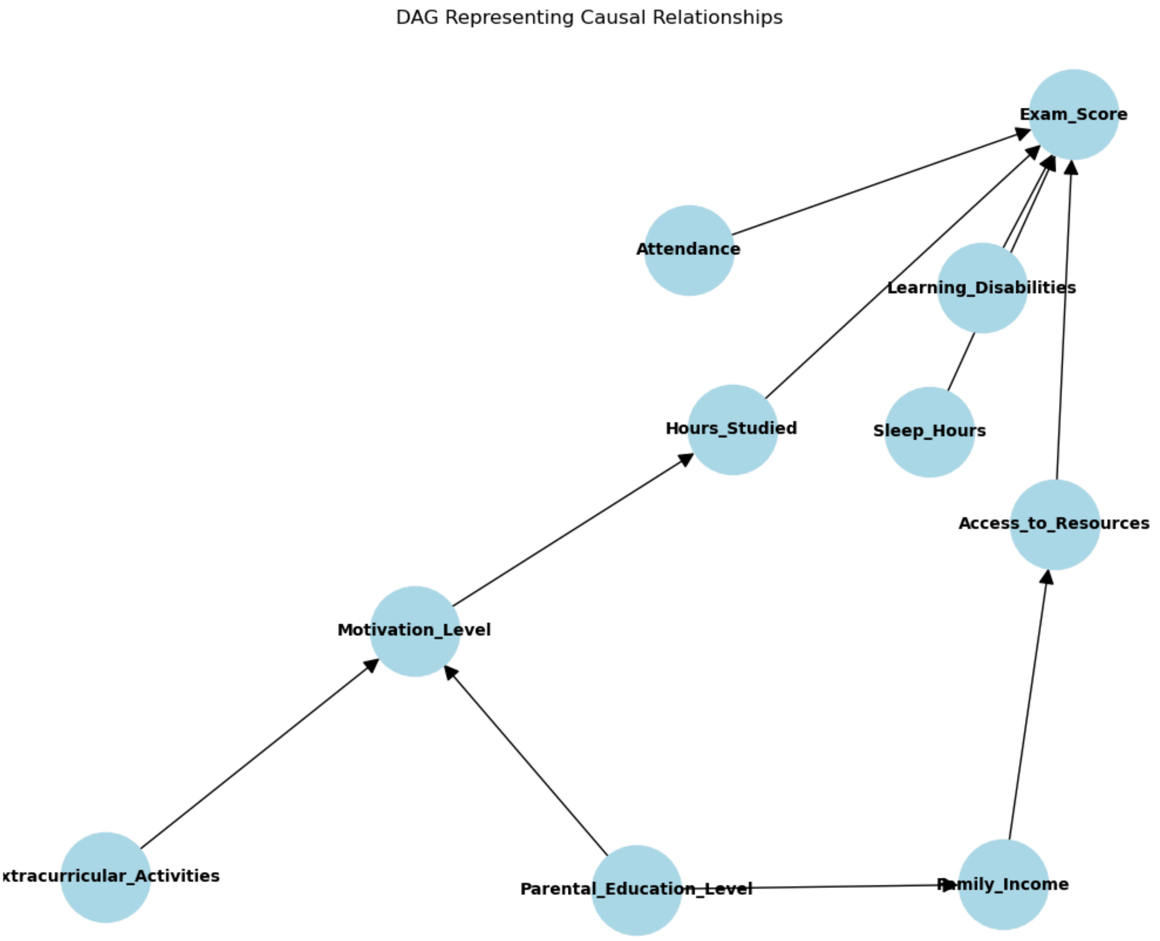
```
Requirement already satisfied: pillow>=6.2.0 in d:\jupyter\lib\site-packages (from m
atplotlib->causal-learn>=0.1.3.0->dowhy) (9.4.0)
Requirement already satisfied: fonttools>=4.22.0 in d:\jupyter\lib\site-packages (fr
om matplotlib->causal-learn>=0.1.3.0->dowhy) (4.25.0)
Requirement already satisfied: kiwisolver>=1.0.1 in d:\jupyter\lib\site-packages (fr
om matplotlib->causal-learn>=0.1.3.0->dowhy) (1.4.4)
Requirement already satisfied: cycler>=0.10 in d:\jupyter\lib\site-packages (from ma
tplotlib->causal-learn>=0.1.3.0->dowhy) (0.11.0)
Requirement already satisfied: pyparsing>=2.3.1 in d:\jupyter\lib\site-packages (fro
m matplotlib->causal-learn>=0.1.3.0->dowhy) (3.0.9)
Installing collected packages: pydot, networkx, cython, causal-learn, dowhy
  Attempting uninstall: networkx
    Found existing installation: networkx 2.8.4
    Uninstalling networkx-2.8.4:
      Successfully uninstalled networkx-2.8.4
Successfully installed causal-learn-0.1.3.8 cython-3.0.11 dowhy-0.11.1 networkx-3.4.
2 pydot-3.0.2
Note: you may need to restart the kernel to use updated packages.
```

In [16]:

```
pip install pgmpy
```

In [3]:

```python
from pgmpy.models import BayesianNetwork
import networkx as nx
import matplotlib.pyplot as plt


model = BayesianNetwork([
    ('Parental_Education_Level', 'Motivation_Level'),
    ('Parental_Education_Level', 'Family_Income'),
    ('Family_Income', 'Access_to_Resources'),
    ('Access_to_Resources', 'Exam_Score'),
    ('Motivation_Level', 'Hours_Studied'),
    ('Hours_Studied', 'Exam_Score'),
    ('Attendance', 'Exam_Score'),
    ('Sleep_Hours', 'Exam_Score'),
    ('Extracurricular_Activities', 'Motivation_Level'),
    ('Learning_Disabilities', 'Exam_Score')
])


graph = nx.DiGraph()
graph.add_nodes_from(model.nodes())
graph.add_edges_from(model.edges())


plt.figure(figsize=(10, 8))
nx.draw(
    graph,
    with_labels=True,
    node_size=3000,
    node_color='lightblue',
    font_size=10,
    font_weight="bold",
    arrowsize=20
)
plt.title("DAG Representing Causal Relationships")
plt.show()
```



In [4]:
```
import numpy as np
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score

# Step 1: Define Structural Equations for SCM
def generate_scm_data(n=1000):
    np.random.seed(42)

    # Exogenous noise variables
    epsilon_resources = np.random.normal(0, 1, n)
    epsilon_motivation = np.random.normal(0, 1, n)
    epsilon_hours = np.random.normal(0, 1, n)
    epsilon_exam = np.random.normal(0, 1, n)

    # Structural Equations
    parental_education = np.random.choice([0, 1, 2], size=n)
    family_income = 3000 + 1000 * parental_education + np.random.normal(0, 500, n)
    access_to_resources = 0.5 + 0.0001 * family_income + epsilon_resources
    extracurricular = np.random.choice([0, 1], size=n)
    motivation_level = 0.3 * parental_education + 0.4 * extracurricular + epsilon_mo
    sleep_hours = np.random.uniform(5, 10, size=n)
    hours_studied = 2 * motivation_level + 0.5 * sleep_hours + epsilon_hours
    attendance = np.random.uniform(50, 100, size=n)
    learning_disabilities = np.random.choice([0, 1], size=n)
    exam_score = (
        10 * hours_studied
        + 5 * access_to_resources
        + 0.3 * attendance
        - 20 * learning_disabilities
        + epsilon_exam
    )
```

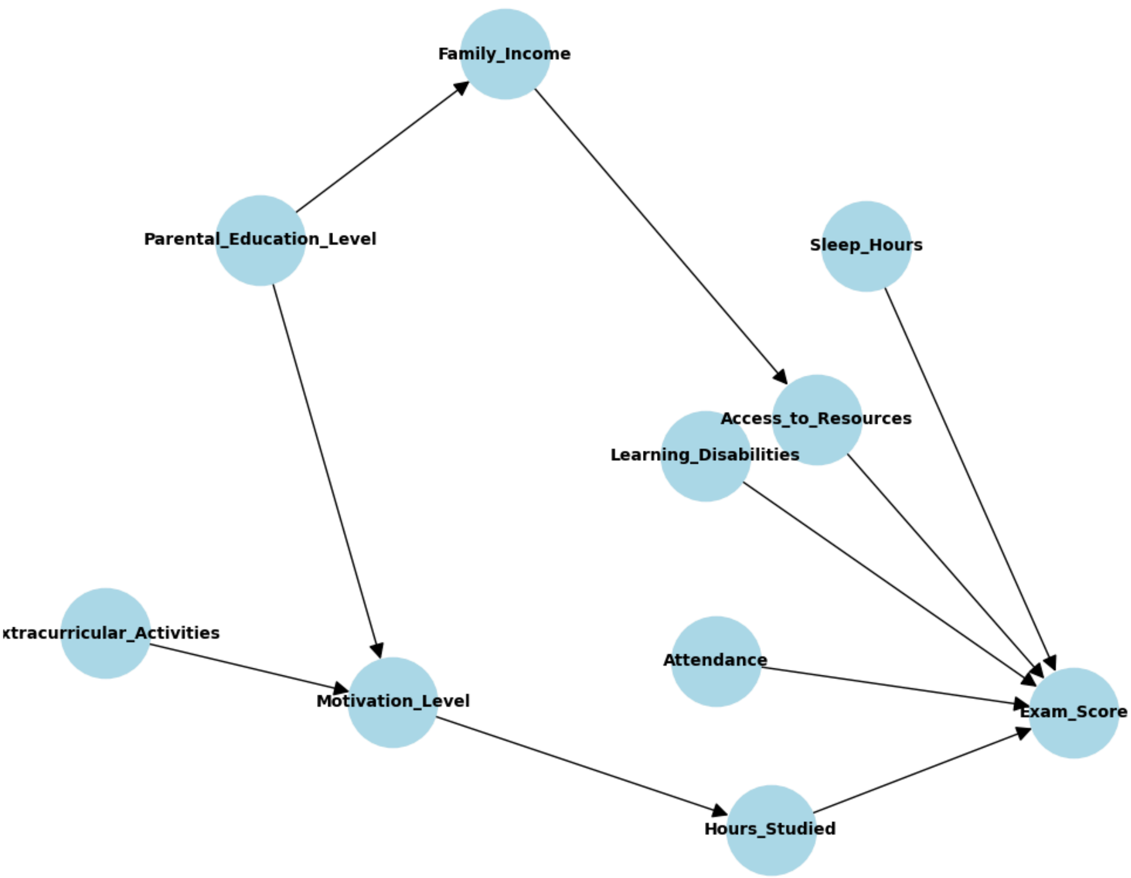
```
    # Combine into a DataFrame
    data = pd.DataFrame({
        "Parental_Education_Level": parental_education,
        "Family_Income": family_income,
        "Access_to_Resources": access_to_resources,
        "Motivation_Level": motivation_level,
        "Hours_Studied": hours_studied,
        "Sleep_Hours": sleep_hours,
        "Attendance": attendance,
        "Extracurricular_Activities": extracurricular,
        "Learning_Disabilities": learning_disabilities,
        "Exam_Score": exam_score
    })
    return data


data = generate_scm_data()

# Step 2: Adjust for Confounders and Analyze Relationships
X = data[["Hours_Studied", "Access_to_Resources", "Attendance", "Learning_Disabiliti
y = data["Exam_Score"]

model = LinearRegression()
model.fit(X, y)
y_pred = model.predict(X)

print("Causal Effect Analysis (Linear Model):")
print(f"Intercept: {model.intercept_}")
for feature, coef in zip(X.columns, model.coef_):
    print(f"{feature}: {coef:.2f}")
print(f"R^2 Score: {r2_score(y, y_pred):.3f}")

# Step 3: Simulate Interventions
# Simulating an intervention: Increase Hours_Studied by 5 hours
data_intervened = data.copy()
data_intervened["Hours_Studied"] += 5

# Predict new Exam Scores after intervention
y_intervened_pred = model.predict(data_intervened[["Hours_Studied", "Access_to_Resou

print("\nSimulating Intervention:")
print(f"Average Exam Score Before Intervention: {data['Exam_Score'].mean():.2f}")
print(f"Average Exam Score After Intervention: {y_intervened_pred.mean():.2f}")

# Step 4: Causal Effect Estimation Using Do-Calculus
# P(Exam_Score | do(Hours_Studied = 10))

data_do_hours = data.copy()
data_do_hours["Hours_Studied"] = 10
y_do_hours_pred = model.predict(data_do_hours[["Hours_Studied", "Access_to_Resources

print("\nDo-Calculus Intervention (Hours_Studied = 10):")
print(f"Average Exam Score After Setting Hours_Studied to 10: {y_do_hours_pred.mean(
```

```
Causal Effect Analysis (Linear Model):
Intercept: 0.34225365409452024
Hours_Studied: 9.99
Access_to_Resources: 4.99
Attendance: 0.30
Learning_Disabilities: -20.08
R^2 Score: 0.999

Simulating Intervention:
Average Exam Score Before Intervention: 65.58
Average Exam Score After Intervention: 115.51

Do-Calculus Intervention (Hours_Studied = 10):
Average Exam Score After Setting Hours_Studied to 10: 116.54
```

In [ ]:

In [5]:

DAG Representing Causal Relationships



In [ ]:

In [ ]:

In [ ]: