In [1]:
```
# Import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
```

In [2]:
```
# Load data
data = pd.read_csv('StudentPerformanceFactors.csv')
data.head()
```

Out[2]:

	Hours_Studied	Attendance	Parental_Involvement	Access_to_Resources	Extracurricular_A
0	23	84	Low	High	
1	19	64	Low	Medium	
2	24	98	Medium	Medium	
3	29	89	Low	Medium	
4	19	92	Medium	Medium	

In [3]:
```
# Check dimmension of data
data.shape
```

Out[3]:
```
(6607, 20)
```

In [4]:
```
# Check for missing values
data.isna().sum()
```

Out[4]:
```
Hours_Studied                 0
Attendance                    0
Parental_Involvement          0
Access_to_Resources           0
Extracurricular_Activities    0
Sleep_Hours                   0
Previous_Scores               0
Motivation_Level              0
Internet_Access               0
Tutoring_Sessions             0
Family_Income                 0
Teacher_Quality              78
School_Type                   0
Peer_Influence                0
Physical_Activity             0
Learning_Disabilities         0
Parental_Education_Level     90
Distance_from_Home           67
Gender                        0
Exam_Score                    0
dtype: int64
```

In [5]:
```
# Remove columns with missing values
data = data.drop(['Teacher_Quality', 'Parental_Education_Level', 'Distance_from_Hom
data.isna().sum()
```

Out[5]:
```
Hours_Studied                 0
Attendance                    0
Parental_Involvement          0
Access_to_Resources           0
Extracurricular_Activities    0
Sleep_Hours                   0
Previous_Scores               0
Motivation_Level              0
Internet_Access               0
Tutoring_Sessions             0
Family_Income                 0
School_Type                   0
Peer_Influence                0
Physical_Activity             0
Learning_Disabilities         0
Gender                        0
Exam_Score                    0
dtype: int64
```

In [6]:
```
# Understand column types
data.dtypes
```

Out[6]:
```
Hours_Studied                 int64
Attendance                    int64
Parental_Involvement         object
Access_to_Resources          object
Extracurricular_Activities   object
Sleep_Hours                   int64
Previous_Scores               int64
Motivation_Level             object
Internet_Access              object
Tutoring_Sessions             int64
Family_Income                object
School_Type                  object
Peer_Influence               object
Physical_Activity             int64
Learning_Disabilities        object
Gender                       object
Exam_Score                    int64
dtype: object
```

In [7]:
```
# Check for duplicates
data.duplicated().sum()
```

Out[7]:
```
0
```

In [8]:
```
# Understand numerical data
data.describe()
```

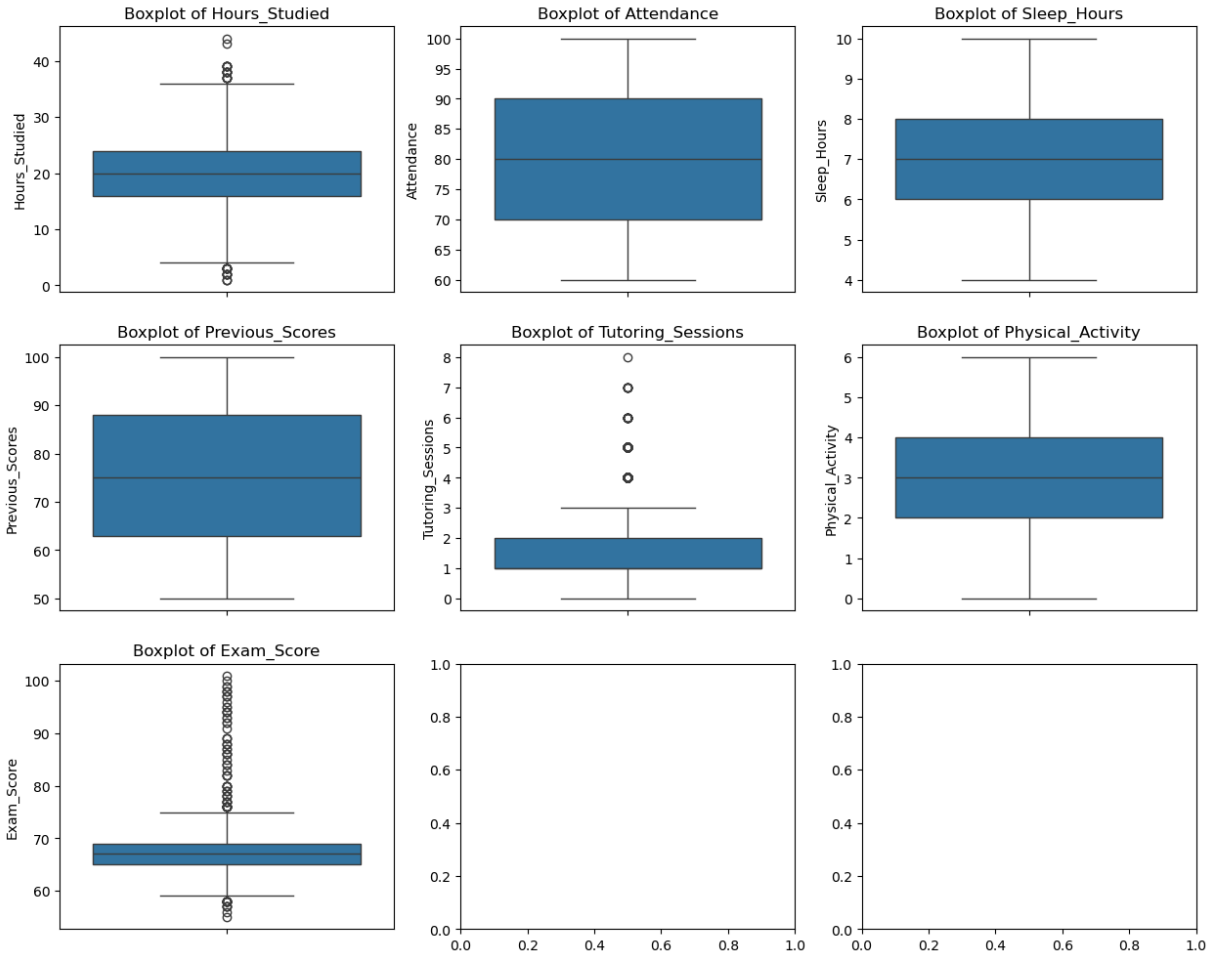
Out[8]:

	Hours_Studied	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessions	Physic
count	6607.000000	6607.000000	6607.00000	6607.000000	6607.000000	6
mean	19.975329	79.977448	7.02906	75.070531	1.493719	
std	5.990594	11.547475	1.46812	14.399784	1.230570	
min	1.000000	60.000000	4.00000	50.000000	0.000000	
25%	16.000000	70.000000	6.00000	63.000000	1.000000	
50%	20.000000	80.000000	7.00000	75.000000	1.000000	
75%	24.000000	90.000000	8.00000	88.000000	2.000000	
max	44.000000	100.000000	10.00000	100.000000	8.000000	

In [9]:
```
# Creating boxplots for outlier detection in numerical variables
fig, axes = plt.subplots(3, 3, figsize=(15,12))
fig.suptitle("Boxplots for Outlier Detection in Exam Score Contribution Variables",

# List of columns to plot
columns_to_plot = ['Hours_Studied', 'Attendance', 'Sleep_Hours', 'Previous_Scores',

# Create boxplots for each variable
for ax, col in zip(axes.flatten(), columns_to_plot):
    sns.boxplot(y=data[col], ax=ax)
```

```
    ax.set_title(f"Boxplot of {col}")

# Adjust layout for better readability
plt.show()
```

Boxplots for Outlier Detection in Exam Score Contribution Variables



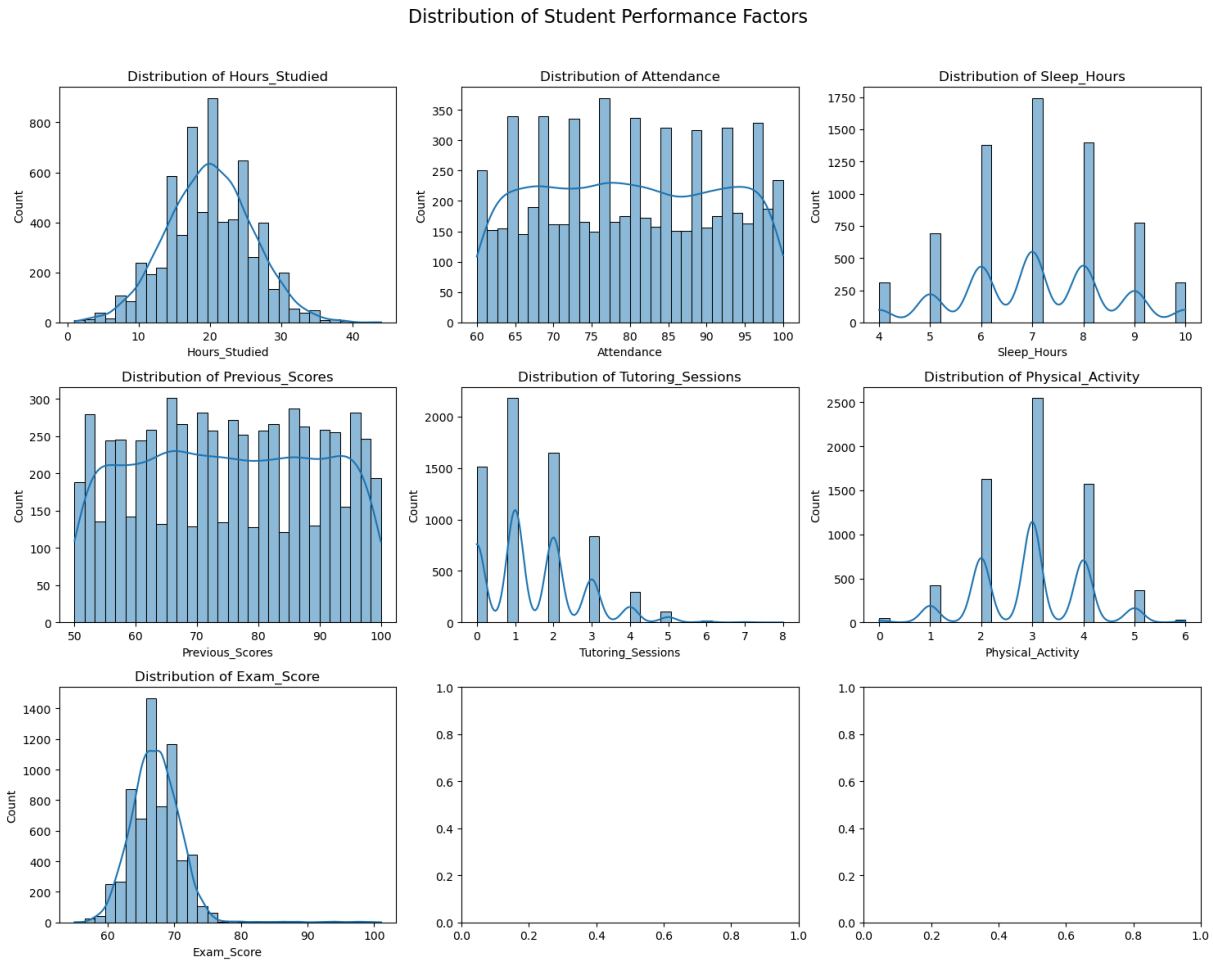
In [10]:

```
# Count Outliers
def count_outliers(column, data):
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = data[column][(data[column] < lower_bound) | (data[column] > upper_bo
    return len(outliers)

# Detect outliers for all numerical features
numerical_features = data.select_dtypes(include=['float64', 'int64']).columns
outliers = []
for col in numerical_features:
    outliers.append({
        'Feature': col,
        'Num of outliers': count_outliers(col, data)
    })
```

```
# Convert to DataFrame and display
outliers_df = pd.DataFrame(outliers)
print(outliers_df)
```

```
            Feature  Num of outliers
0      Hours_Studied               43
1         Attendance                0
2        Sleep_Hours                0
3    Previous_Scores                0
4  Tutoring_Sessions              430
5  Physical_Activity                0
6         Exam_Score              104
```

In [11]:
```
# Creating distribution plots for Student Performance Factors
fig, axes = plt.subplots(3, 3, figsize=(15, 12))
fig.suptitle("Distribution of Student Performance Factors", fontsize=16)

# List of columns to plot
columns_to_plot = ['Hours_Studied', 'Attendance', 'Sleep_Hours', 'Previous_Scores',
for ax, col in zip(axes.flatten(), columns_to_plot):
    sns.histplot(data[col], bins=30, kde=True, ax=ax)
    ax.set_title(f"Distribution of {col}")

# Adjust layout for better readability
plt.tight_layout(rect=[0, 0, 1, 0.96])
plt.show()
```



In [12]:
```
# One-hot encode categorical columns
data_dummies = pd.get_dummies(data, columns=['Parental_Involvement', 'Access_to_Res
```

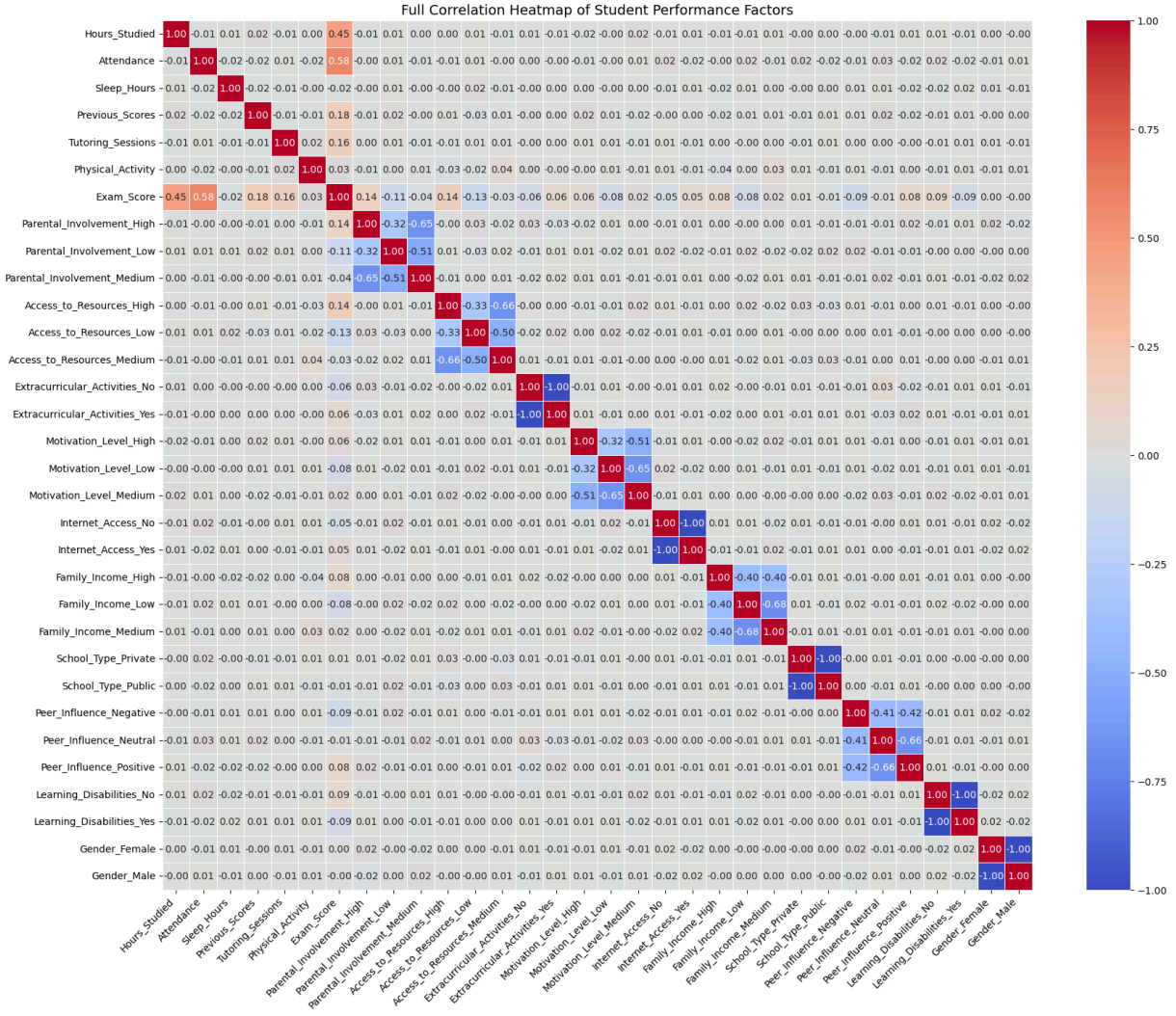
In [13]:
```
# Show Data with Dummy Variables
data_dummies.head()
```

Out[13]:

	Hours_Studied	Attendance	Sleep_Hours	Previous_Scores	Tutoring_Sessions	Physical_A
0	23	84	7	73	0	
1	19	64	8	59	2	
2	24	98	7	91	2	
3	29	89	8	98	1	
4	19	92	6	65	3	

5 rows × 32 columns

In [14]:
```
# Create Correlation Heatmap to conduct preliminary analysis
plt.figure(figsize=(20, 16))
heatmap = sns.heatmap(data_dummies.corr(), annot=True, cmap='coolwarm', fmt=".2f",

# Improve layout and readability
plt.title("Full Correlation Heatmap of Student Performance Factors", fontsize=14)
plt.xticks(rotation=45, ha="right", fontsize=10)
plt.yticks(fontsize=10)

plt.show()
```



In [15]:
```
# Create feature and target variables
X = data_dummies.drop('Exam_Score', axis=1)
y = data_dummies['Exam_Score']
```

In [16]:
```
# Train-test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.2, random_stat
```

In [17]:
```
# Standardize numerical Feataures
scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [18]:
```
# Identify which models will be tested with the data
models = {
      "Linear Regression": LinearRegression(),
    "Random Forest": RandomForestRegressor(random_state=42),
    "Gradient Boosting": GradientBoostingRegressor(random_state=42)
}
```

In [19]:
```
# Train and evaluate each model
results = {}
```

```
for name, model in models.items():
    model.fit(X_train_scaled, y_train)
    y_pred = model.predict(X_test_scaled)

    rmse = np.sqrt(mean_squared_error(y_test, y_pred))
    mae = mean_absolute_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)


    results[name] = {"RMSE": rmse, "MAE": mae, "R^2": r2}

results = pd.DataFrame(results)
results
```

Out[19]:

	Linear Regression	Random Forest	Gradient Boosting
RMSE	1.898981	2.174966	1.973750
MAE	0.672551	1.113313	0.868548
R^2	0.744881	0.665338	0.724395

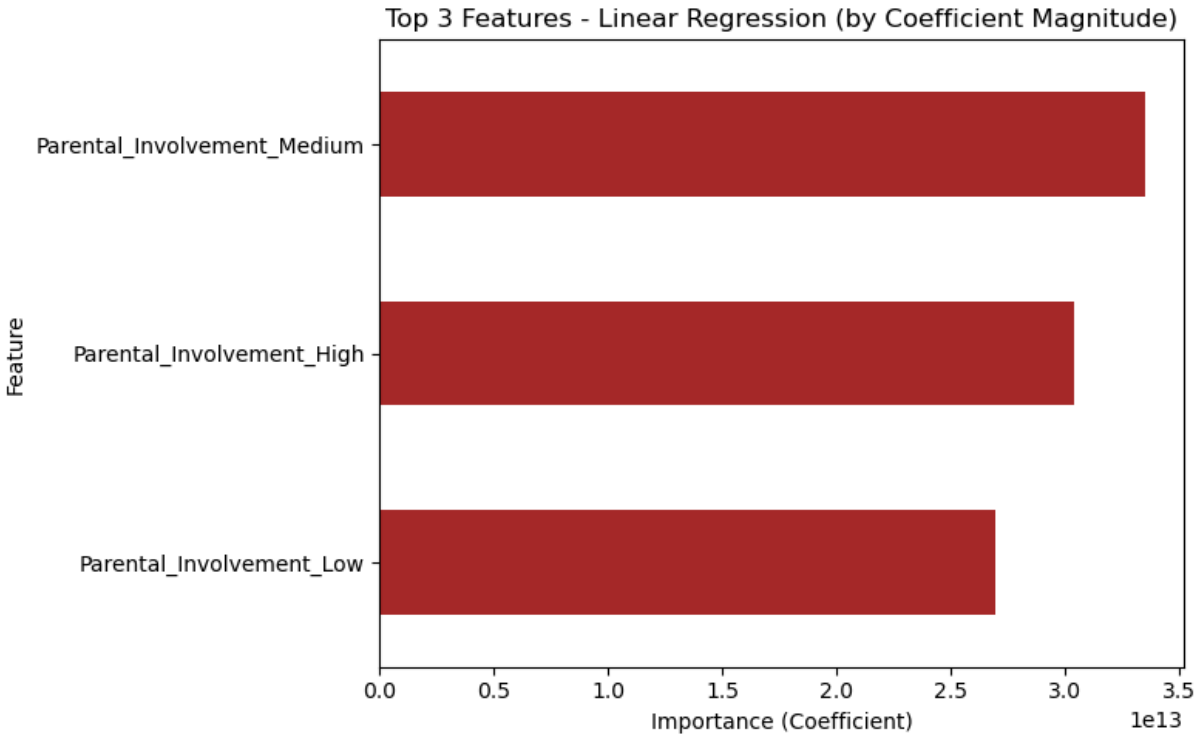
In [20]:
```
# Get top 3 features for each model

# Linear Regression - based on absolute value of coefficients
lr_coeffs = pd.Series(np.abs(models["Linear Regression"].coef_), index=X.columns)
top3_lr = lr_coeffs.sort_values(ascending=False).head(3)

# Random Forest - based on feature importance
rf_importances = pd.Series(models["Random Forest"].feature_importances_, index=X.co
top3_rf = rf_importances.sort_values(ascending=False).head(3)

# Gradient Boosting - based on feature importance
gb_importances = pd.Series(models["Gradient Boosting"].feature_importances_, index=
top3_gb = gb_importances.sort_values(ascending=False).head(3)

# Combine results into a single DataFrame for display
top_features_df = pd.DataFrame({
    "Linear Regression": top3_lr.index,
    "Random Forest": top3_rf.index,
    "Gradient Boosting": top3_gb.index
})
top_features_df
```

Out[20]:

	Linear Regression	Random Forest	Gradient Boosting
0	Parental_Involvement_Medium	Attendance	Attendance
1	Parental_Involvement_High	Hours_Studied	Hours_Studied
2	Parental_Involvement_Low	Previous_Scores	Previous_Scores

In [21]:
```
# Plot the top 3 features by importance (Linear Regression)
plt.figure(figsize=(8, 5))
```

```
top3_lr.sort_values().plot(kind='barh', color='brown')
plt.title('Top 3 Features - Linear Regression (by Coefficient Magnitude)')
plt.xlabel('Importance (Coefficient)')
plt.ylabel('Feature')
plt.tight_layout()
plt.show()
```



In [ ]: