Student Performance Analysis

Project Objective

The objective of this project is to analyze student academic performance and identify key demographic, socio-economic, and behavioral factors that influence exam scores. This analysis aims to derive actionable academic insights using Exploratory Data Analysis (EDA).

In [2]:
```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

plt.style.use('default')
sns.set_theme(style="whitegrid")

import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
df = pd.read_csv("StudentsPerformance.csv")
df.head()
```

Out[3]:

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reading score	writing score
0	female	group B	bachelor's degree	standard	none	72	72	74
1	female	group C	some college	standard	completed	69	90	88
2	female	group B	master's degree	standard	none	90	95	93
3	male	group A	associate's degree	free/reduced	none	47	57	44
4	male	group C	some college	standard	none	76	78	75

In [4]:
```
df.shape
```

Out[4]:
```
(1000, 8)
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 8 columns):
 #   Column                       Non-Null Count  Dtype 
---  ------                       --------------  ----- 
 0   gender                       1000 non-null   object
 1   race/ethnicity               1000 non-null   object
 2   parental level of education  1000 non-null   object
 3   lunch                        1000 non-null   object
 4   test preparation course      1000 non-null   object
 5   math score                   1000 non-null   int64 
 6   reading score                1000 non-null   int64 
 7   writing score                1000 non-null   int64 
dtypes: int64(3), object(5)
memory usage: 62.6+ KB
```

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

Out[6]:

	math score	reading score	writing score
count	1000.00000	1000.000000	1000.000000
mean	66.08900	69.169000	68.054000
std	15.16308	14.600192	15.195657
min	0.00000	17.000000	10.000000
25%	57.00000	59.000000	57.750000
50%	66.00000	70.000000	69.000000
75%	77.00000	79.000000	79.000000
max	100.00000	100.000000	100.000000

In [7]:
```
df.columns
```

Out[7]:
```
Index(['gender', 'race/ethnicity', 'parental level of education', 'lunch',
       'test preparation course', 'math score', 'reading score',
       'writing score'],
      dtype='object')
```

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

Out[8]:
```
gender                         0
race/ethnicity                 0
parental level of education    0
lunch                          0
test preparation course        0
math score                     0
reading score                  0
writing score                  0
dtype: int64
```

In [9]:
```
df.duplicated().sum()
```

Out[9]:
```
np.int64(0)
```

In [10]:
```
score_columns = ['math score', 'reading score', 'writing score']
```

```
df[score_columns].describe()
```

Out[10]:

	math score	reading score	writing score
count	1000.00000	1000.000000	1000.000000
mean	66.08900	69.169000	68.054000
std	15.16308	14.600192	15.195657
min	0.00000	17.000000	10.000000
25%	57.00000	59.000000	57.750000
50%	66.00000	70.000000	69.000000
75%	77.00000	79.000000	79.000000
max	100.00000	100.000000	100.000000

In [11]:
```
df['average_score'] = df[score_columns].mean(axis=1)
df.head()
```

Out[11]:

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reading score	writing score
0	female	group B	bachelor's degree	standard	none	72	72	74
1	female	group C	some college	standard	completed	69	90	88
2	female	group B	master's degree	standard	none	90	95	93
3	male	group A	associate's degree	free/reduced	none	47	57	44
4	male	group C	some college	standard	none	76	78	75

In [12]:
```
categorical_columns = df.select_dtypes(include='object').columns
categorical_columns
```

Out[12]:
```
Index(['gender', 'race/ethnicity', 'parental level of education', 'lunch',
       'test preparation course'],
      dtype='object')
```

In [13]:
```
df.shape
```

Out[13]:
```
(1000, 9)
```

In [14]:
```
df.sample(5)
```

Out[14]:

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reading score	writing score
315	male	group C	high school	standard	none	71	66	65
257	male	group C	associate's degree	standard	completed	78	77	77
984	female	group C	some high school	standard	none	74	75	82
848	female	group C	high school	standard	none	59	72	68
115	male	group C	high school	standard	none	84	77	74

Data Cleaning Summary

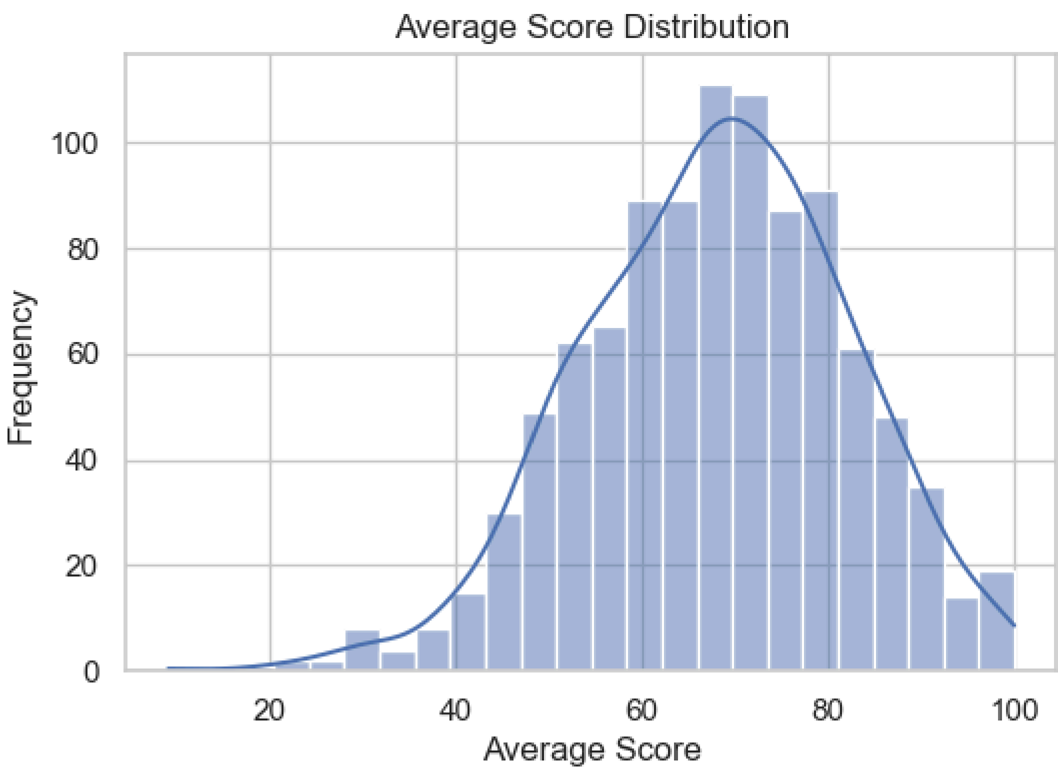
- The dataset was examined for missing values and duplicates.
- No missing or duplicate records were found.
- Score ranges were validated to ensure data consistency.
- A new feature, `average_score`, was engineered to represent overall academic performance.
- Categorical and numerical features were identified for further analysis.

In [15]:

```
plt.figure(figsize=(15,5))

plt.subplot(1,3,1)
sns.histplot(df['math score'], kde=True)
plt.title('Math Score Distribution')

plt.subplot(1,3,2)
sns.histplot(df['reading score'], kde=True)
plt.title('Reading Score Distribution')

plt.subplot(1,3,3)
sns.histplot(df['writing score'], kde=True)
plt.title('Writing Score Distribution')

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

- Math scores show relatively higher variability compared to reading and writing.
- Reading and writing scores are more symmetrically distributed, indicating consistent performance.
- Overall, students tend to perform slightly better in reading and writing than in mathematics.

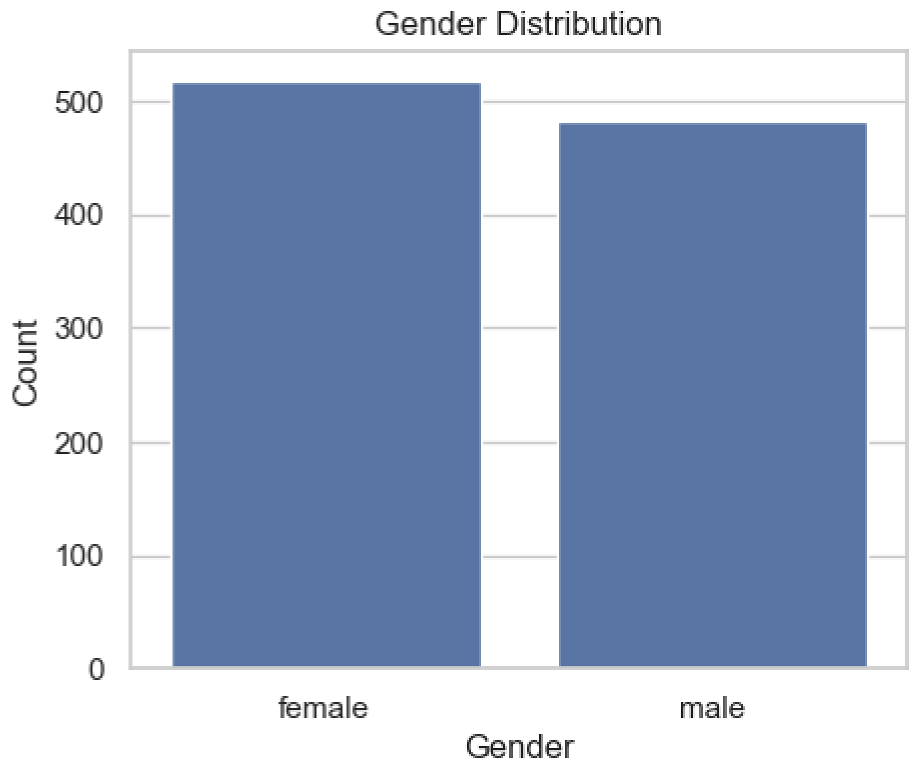
In [16]:
```
plt.figure(figsize=(6,4))
sns.histplot(df['average_score'], kde=True)
plt.title('Average Score Distribution')
plt.xlabel('Average Score')
plt.ylabel('Frequency')
plt.show()
```



- The average score distribution is approximately normal.
- Most students cluster around the mid-range scores, indicating moderate overall academic performance.

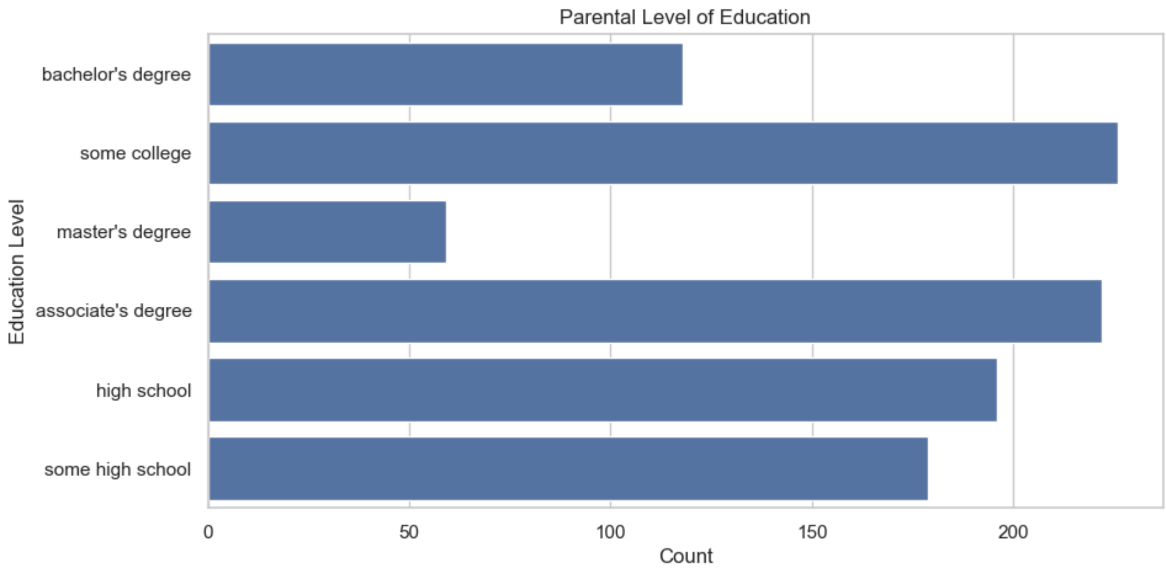
In [17]:
```
plt.figure(figsize=(5,4))
sns.countplot(x='gender', data=df)
```

```
plt.title('Gender Distribution')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()
```



- The dataset contains a nearly balanced distribution of male and female students.
- This balance ensures fair comparative analysis between genders in later stages.

In [18]:
```
plt.figure(figsize=(10,5))
sns.countplot(y='parental level of education', data=df)
plt.title('Parental Level of Education')
plt.xlabel('Count')
plt.ylabel('Education Level')
plt.show()
```



- Most parents have education levels ranging from some college to associate's degree.
- Higher education levels are less frequent, which may influence academic support availability.

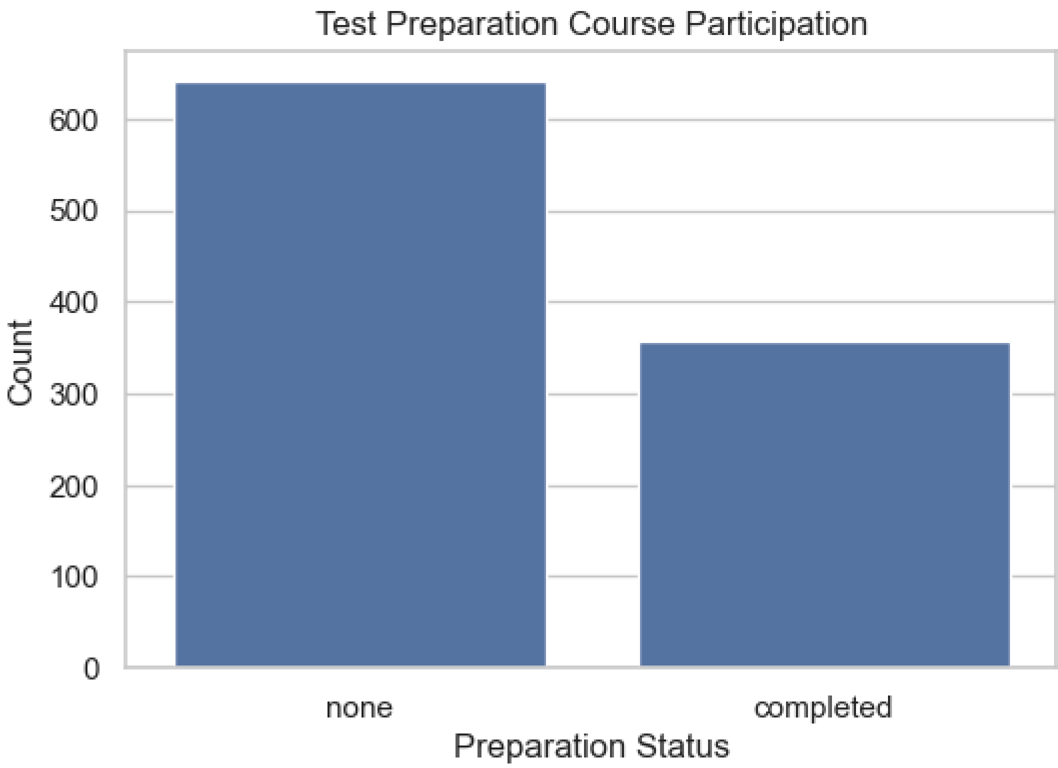
In [19]:

```
plt.figure(figsize=(5,4))
sns.countplot(x='lunch', data=df)
plt.title('Lunch Type Distribution')
plt.xlabel('Lunch Type')
plt.ylabel('Count')
plt.show()
```

- A higher proportion of students receive standard lunch compared to free/reduced lunch.
- Lunch type may act as a proxy indicator for socio-economic status.

In [20]:

```
plt.figure(figsize=(6,4))
sns.countplot(x='test preparation course', data=df)
plt.title('Test Preparation Course Participation')
plt.xlabel('Preparation Status')
plt.ylabel('Count')
plt.show()
```

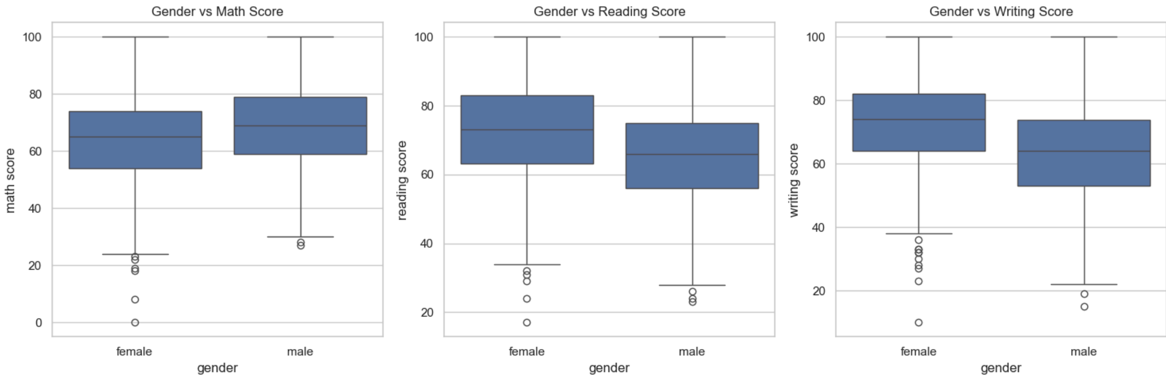


- A significant number of students did not complete the test preparation course.
- This variable is expected to show a strong relationship with academic performance.

Univariate Analysis Summary

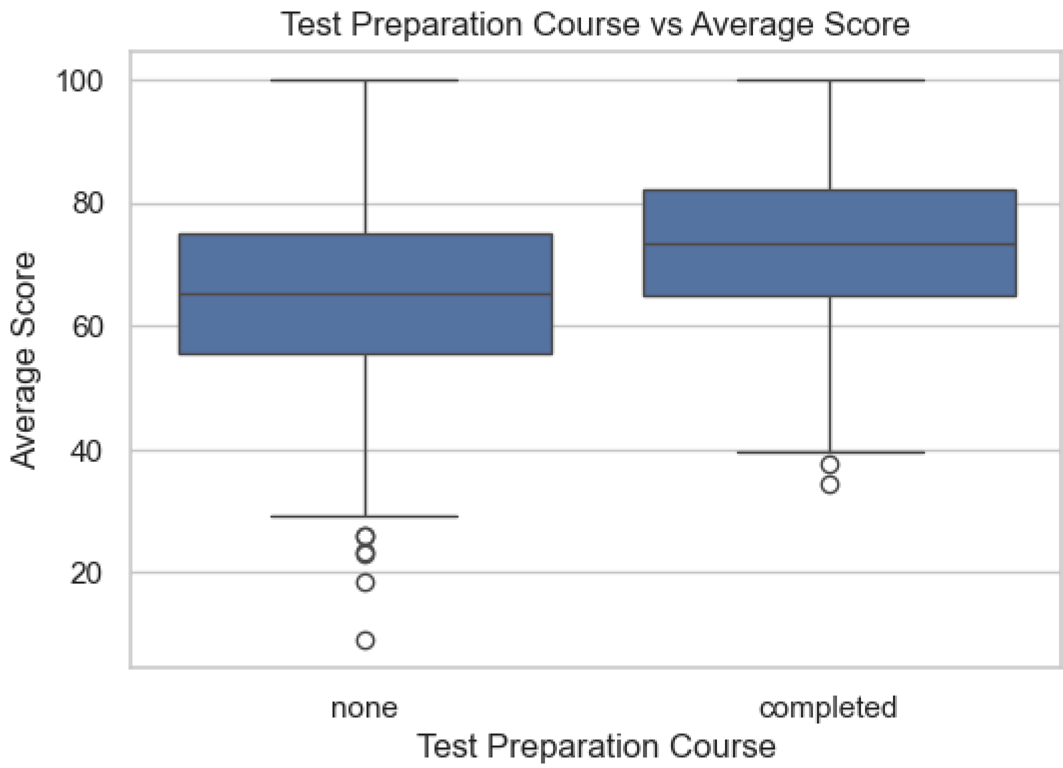
- Student scores vary across subjects, with mathematics showing the highest variability.
- The dataset is demographically balanced in terms of gender.
- Parental education and socio-economic indicators show diverse distributions.
- Several categorical variables have the potential to influence student performance and will be analyzed further.

In [21]:
```
plt.figure(figsize=(15,5))

plt.subplot(1,3,1)
sns.boxplot(x='gender', y='math score', data=df)
plt.title('Gender vs Math Score')

plt.subplot(1,3,2)
sns.boxplot(x='gender', y='reading score', data=df)
plt.title('Gender vs Reading Score')

plt.subplot(1,3,3)
sns.boxplot(x='gender', y='writing score', data=df)
plt.title('Gender vs Writing Score')

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



- Female students tend to outperform male students in reading and writing scores.
- Male students show slightly higher median scores in mathematics.
- Gender-based performance differences vary by subject rather than overall ability.

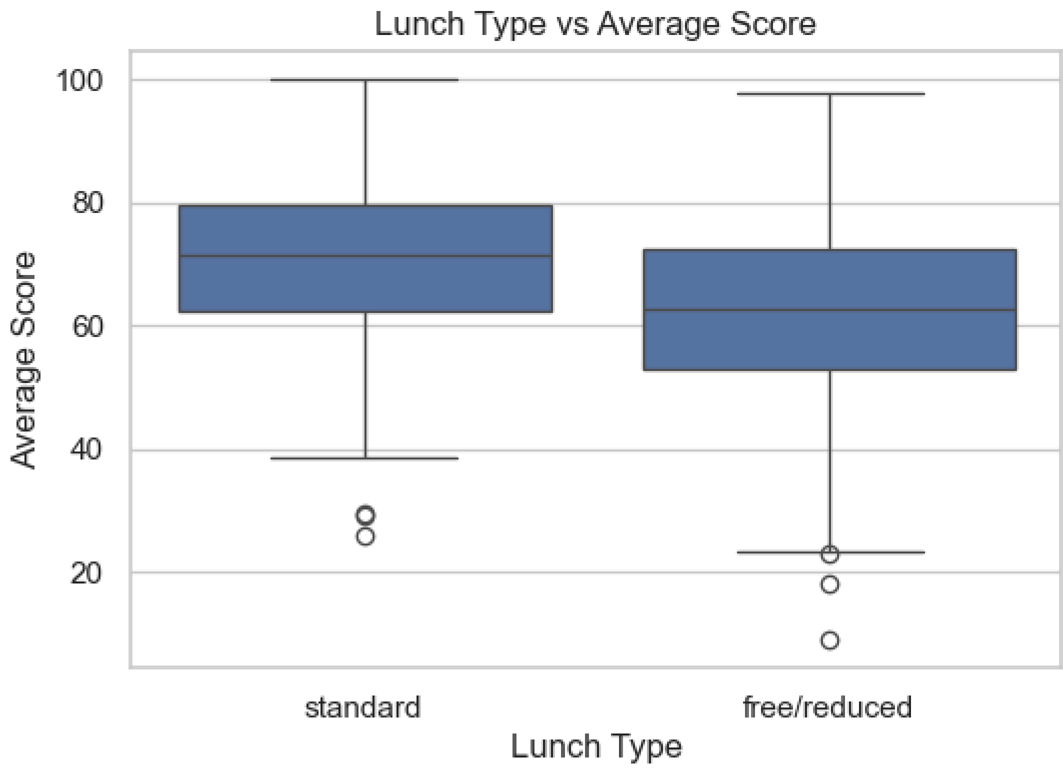
In [22]:
```
plt.figure(figsize=(6,4))
sns.boxplot(x='test preparation course', y='average_score', data=df)
plt.title('Test Preparation Course vs Average Score')
plt.xlabel('Test Preparation Course')
plt.ylabel('Average Score')
plt.show()
```



- Students who completed the test preparation course have significantly higher average scores.
- This indicates structured preparation has a strong positive impact on academic performance.

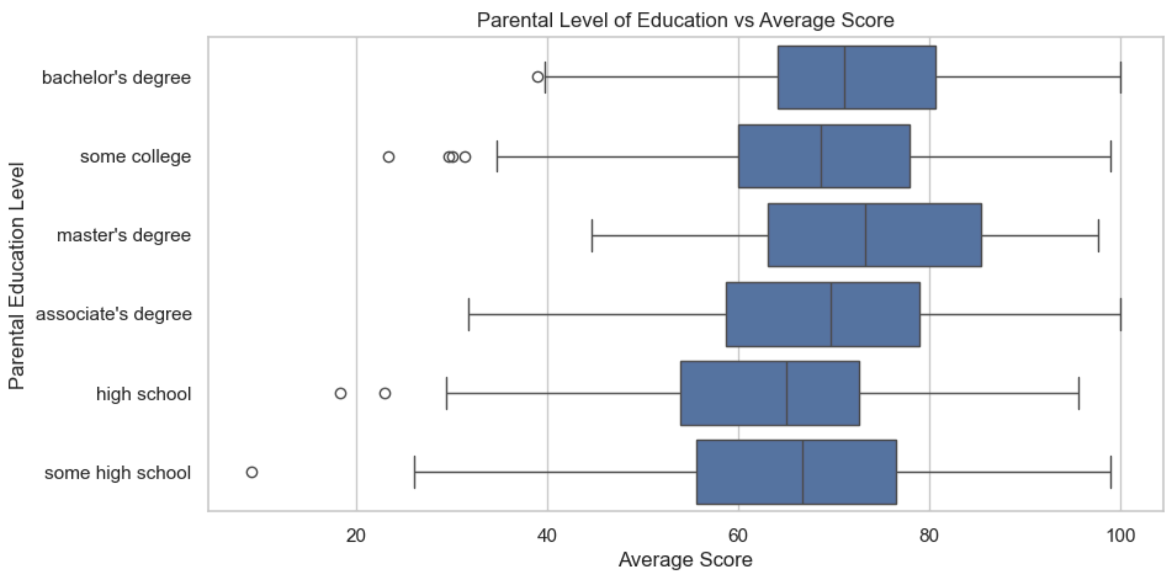
In [23]:
```
plt.figure(figsize=(6,4))
sns.boxplot(x='lunch', y='average_score', data=df)
plt.title('Lunch Type vs Average Score')
```

```
plt.xlabel('Lunch Type')
plt.ylabel('Average Score')
plt.show()
```



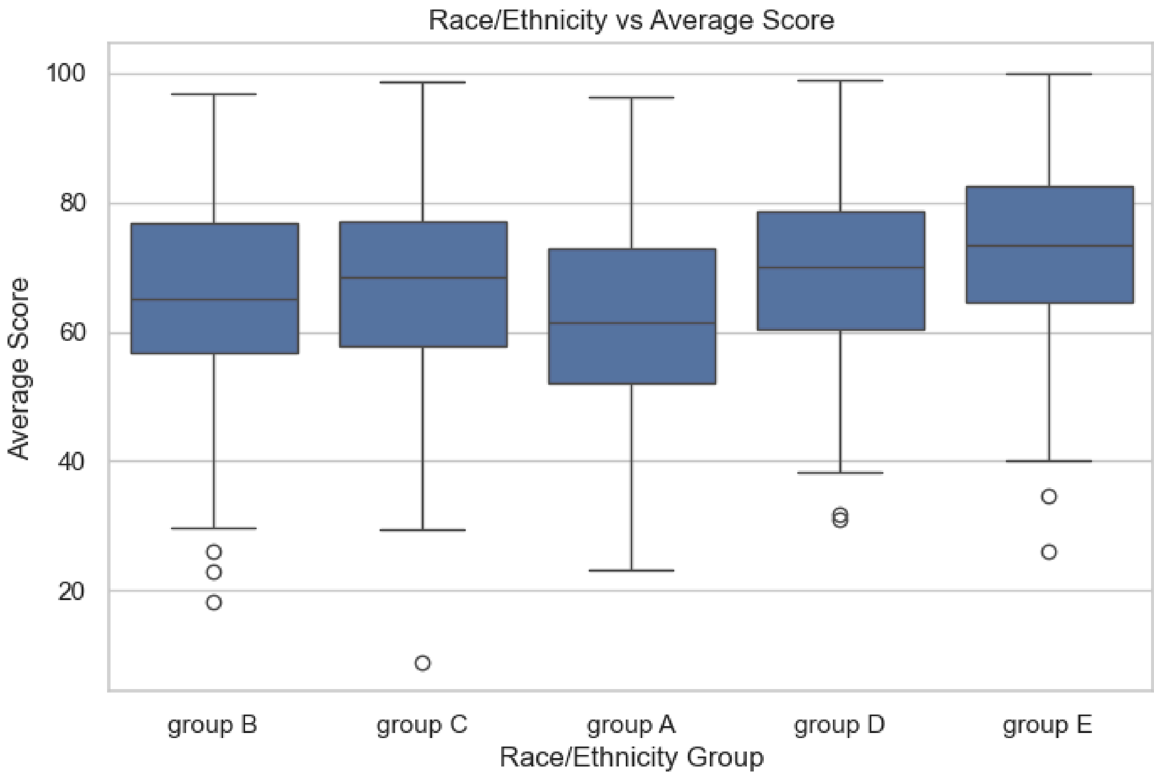
- Students receiving standard lunch generally score higher than those with free/reduced lunch.
- Lunch type appears to correlate with socio-economic factors affecting performance.

In [24]:
```
plt.figure(figsize=(10,5))
sns.boxplot(y='parental level of education', x='average_score', data=df)
plt.title('Parental Level of Education vs Average Score')
plt.xlabel('Average Score')
plt.ylabel('Parental Education Level')
plt.show()
```



- Higher parental education levels are associated with better student performance.
- Students whose parents have higher education levels tend to achieve higher average scores.

In [25]:
```
plt.figure(figsize=(8,5))
sns.boxplot(x='race/ethnicity', y='average_score', data=df)
plt.title('Race/Ethnicity vs Average Score')
plt.xlabel('Race/Ethnicity Group')
plt.ylabel('Average Score')
plt.show()
```



- Performance varies across different race/ethnicity groups.
- These differences may reflect underlying socio-economic and educational resource disparities.

Bivariate Analysis Summary

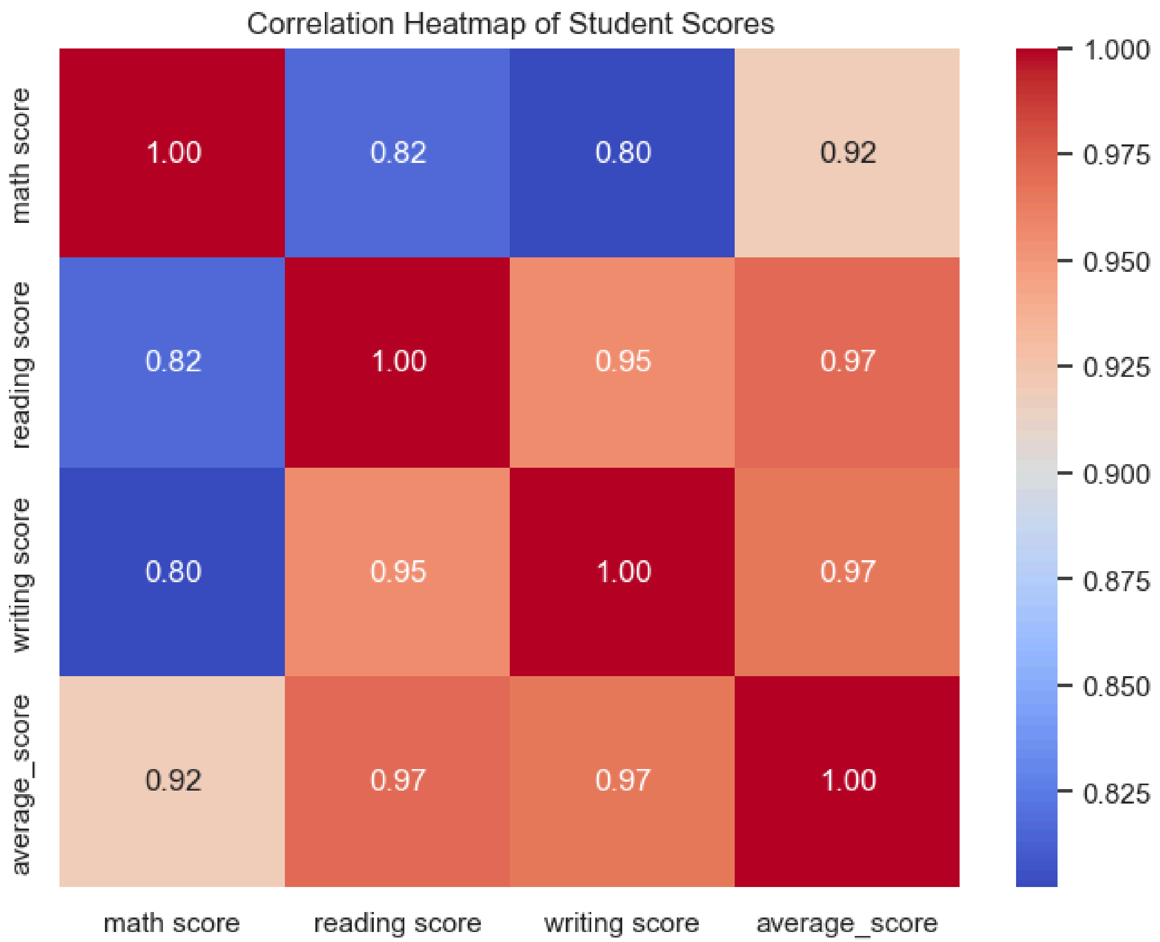
- Academic performance is influenced by demographic, socio-economic, and behavioral factors.
- Test preparation courses show the strongest positive relationship with performance.
- Parental education and lunch type significantly correlate with student outcomes.
- Gender-based performance differences are subject-specific rather than overall.

In [26]:
```
numeric_df = df[['math score', 'reading score', 'writing score', 'average_score'
numeric_df.corr()
```

Out[26]:

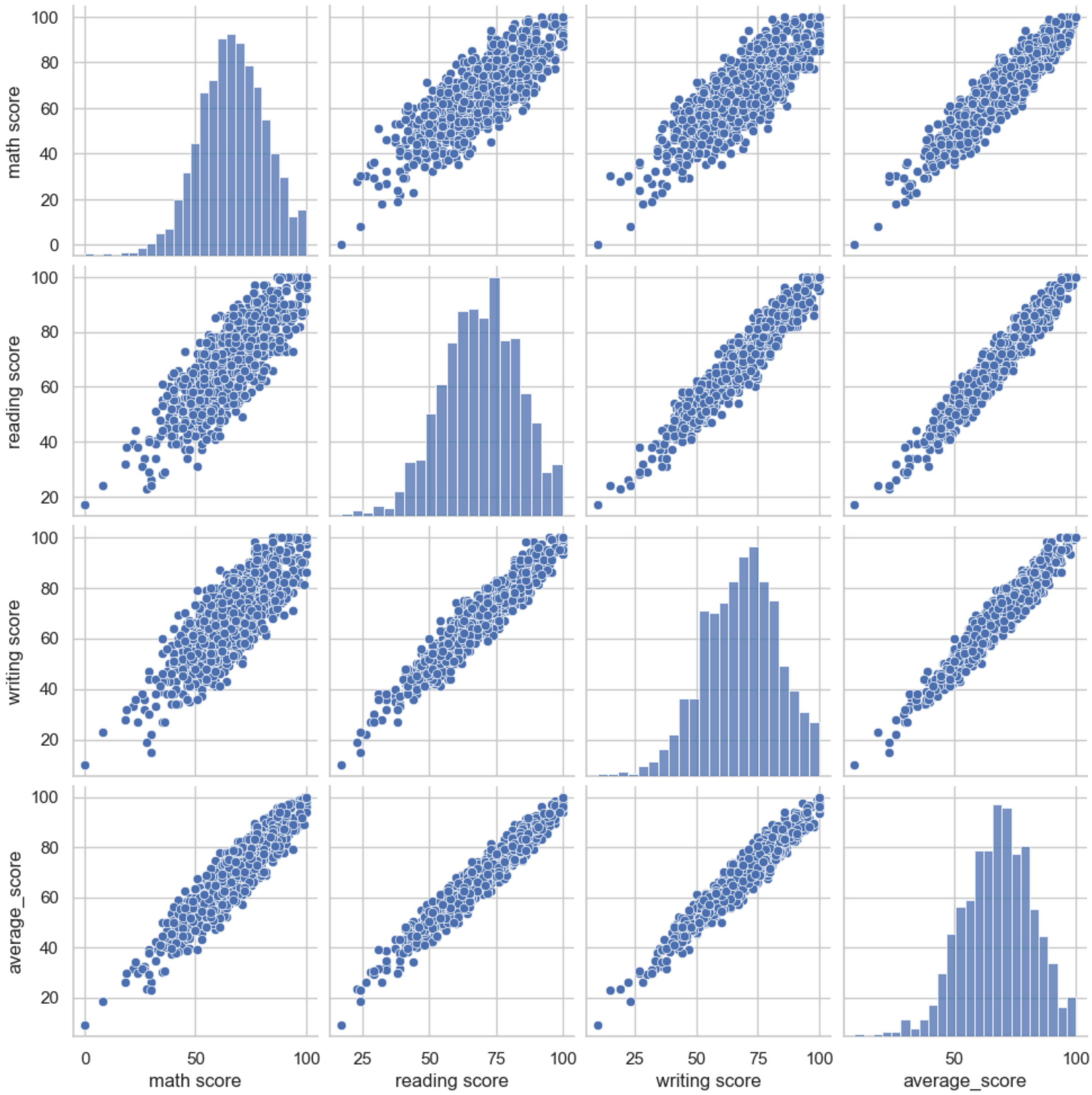
	math score	reading score	writing score	average_score
math score	1.000000	0.817580	0.802642	0.918746
reading score	0.817580	1.000000	0.954598	0.970331
writing score	0.802642	0.954598	1.000000	0.965667
average_score	0.918746	0.970331	0.965667	1.000000

In [27]:
```
plt.figure(figsize=(8,6))
sns.heatmap(numeric_df.corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap of Student Scores')
plt.show()
```



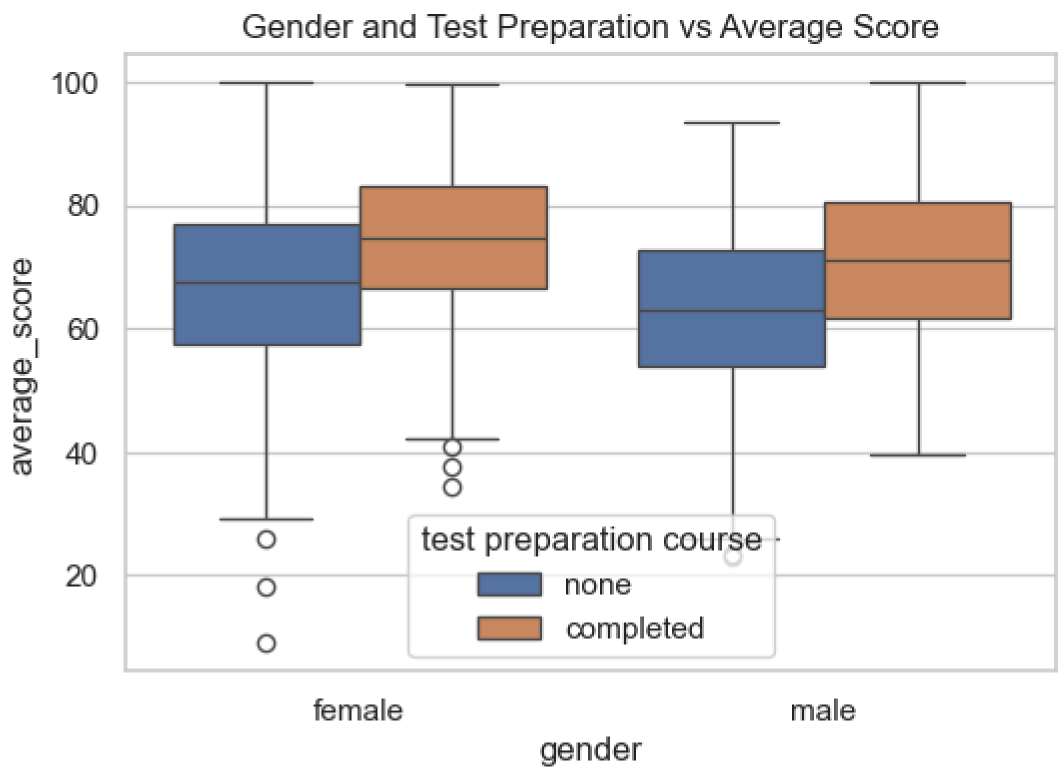
- Strong positive correlations exist between reading and writing scores.
- Average score is highly correlated with all individual subject scores.
- Mathematics shows slightly lower correlation with language-based subjects, indicating subject-specific skill differences.

In [28]:
```
sns.pairplot(numeric_df)
plt.show()
```



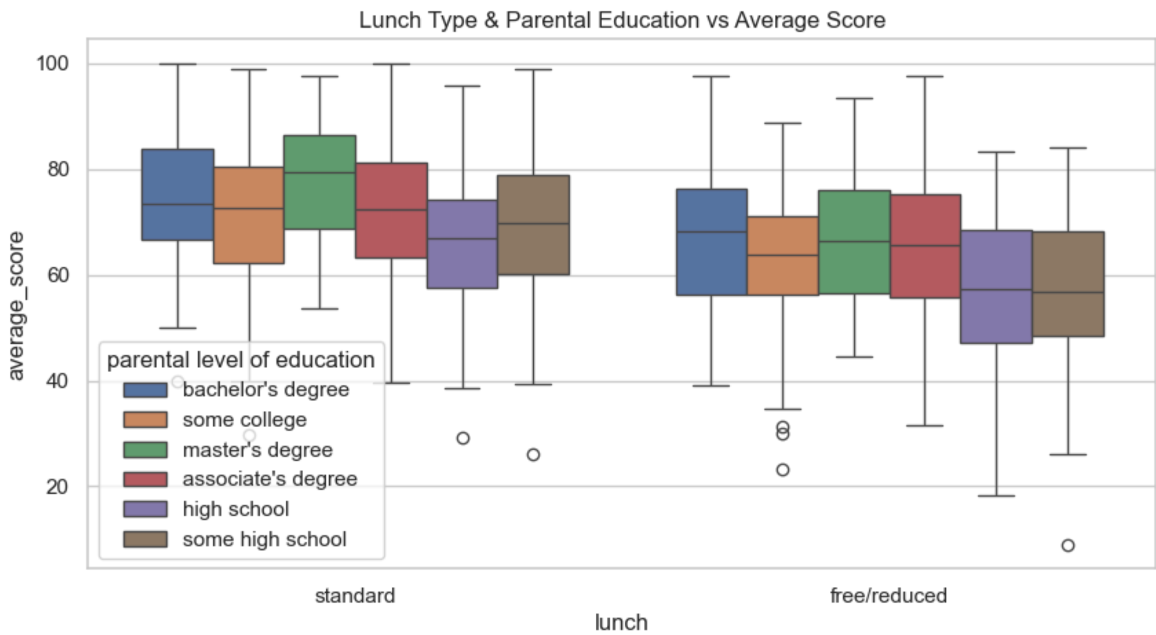
- Linear relationships are observed among all score variables.
- Reading and writing scores exhibit the strongest linear association.
- No extreme outliers are evident, indicating data consistency.

In [29]:
```
plt.figure(figsize=(6,4))
sns.boxplot(x='gender', y='average_score', hue='test preparation course', data=d
plt.title('Gender and Test Preparation vs Average Score')
plt.show()
```



- Test preparation consistently improves performance across both genders.
- Gender differences reduce significantly among students who completed test preparation.
- Structured academic support mitigates performance disparities.

In [30]:
```
plt.figure(figsize=(10,5))
sns.boxplot(x='lunch', y='average_score', hue='parental level of education', dat
plt.title('Lunch Type & Parental Education vs Average Score')
plt.show()
```



- Students with standard lunch and higher parental education achieve the highest scores.

- Socio-economic factors and parental background jointly influence academic outcomes.

Multivariate Analysis Summary

- Student performance is influenced by a combination of academic preparation, socio-economic status, and parental background.
- Test preparation emerges as the most impactful controllable factor.
- Strong correlations among subject scores suggest consistent academic ability patterns.
- Multivariate analysis confirms that targeted interventions can reduce performance gaps.

Key Insights & Findings

1. **Subject-wise Performance Patterns**
    - Students generally perform better in reading and writing compared to mathematics.
    - Mathematics scores show higher variability, indicating uneven conceptual understanding.
2. **Impact of Test Preparation**
    - Test preparation course completion has a strong positive impact on academic performance.
    - Students who completed the course consistently scored higher across all subjects.
3. **Gender-Based Trends**
    - Female students outperform male students in reading and writing.
    - Male students show slightly better performance in mathematics.
    - Overall academic ability is comparable across genders, with subject-specific differences.
4. **Socio-Economic Influence**
    - Students receiving standard lunch perform better than those with free/reduced lunch.
    - Lunch type serves as an indicator of socio-economic background affecting outcomes.
5. **Parental Education Effect**
    - Higher parental education levels are associated with improved student performance.
    - Students whose parents hold higher degrees tend to achieve higher average scores.
6. **Correlation Between Subjects**

- Strong positive correlations exist between reading and writing scores.
- Average score is highly correlated with all individual subject scores, validating it as a holistic metric.

7. **Multivariate Relationships**

- Test preparation reduces performance gaps across genders.
- Combined effects of parental education and socio-economic status significantly influence academic success.

Conclusion

This analysis explored multiple demographic, socio-economic, and academic factors influencing student performance. The findings indicate that while inherent differences exist across subjects and demographics, structured academic support such as test preparation courses plays a critical role in improving outcomes.

Socio-economic background and parental education significantly affect performance, highlighting the importance of targeted educational interventions. Overall, the analysis demonstrates that student performance is shaped by a combination of controllable and non-controllable factors, with preparation and support being key drivers of success.

Future Scope

- Apply predictive modeling to forecast student performance using machine learning algorithms.
- Include attendance, study hours, and psychological factors for deeper analysis.
- Perform longitudinal studies to track performance trends over time.
- Use clustering techniques to group students based on learning patterns.
- Develop recommendation systems for personalized academic improvement plans.

In [ ]:

```
```