Student Performance Analysis

🟦 Abstract

This project analyzes student academic performance data to identify pass/fail patterns, subject-wise strengths and weaknesses, and the impact of attendance on academic outcomes. Using statistical analysis and visual exploration, the study aims to generate actionable insights that can help educational institutions improve learning outcomes and student support strategies.

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Domain: Education Analytics

Tools & Technologies Used:

- Python
- Pandas & NumPy
- Matplotlib & Seaborn
- Plotly (Interactive Analysis)
- Jupyter Notebook
- Modular Python Architecture
- OS-independent file handling using `pathlib`

🟦 Executive Summary

This analysis evaluates student performance using examination scores, attendance data, and demographic attributes. The objective is to identify academic trends, measure the effect of attendance on scores, and highlight subjects that require targeted academic intervention. All insights are derived directly from the dataset without assumptions or synthetic data.

🟦 Introduction

Business Problem

Educational institutions collect extensive student performance data, but without structured analysis, it is difficult to identify learning gaps, predict academic risks, and design effective interventions.

Objectives

- Calculate overall pass and fail rates
- Analyze subject-wise academic performance
- Study the relationship between attendance and scores
- Identify high-performing and weak subjects
- Provide data-driven academic recommendations

🟦 Dataset Description

The dataset contains academic records of students, including subject scores, attendance percentage, and demographic information.

Key Attributes

- Student_ID – Unique student identifier
- Gender – Student gender
- Attendance – Attendance percentage
- Subject scores – Academic scores per subject
- Total / Average score – Overall academic performance
- Result – Pass or Fail status

Methodology

Analytics Pipeline

1. Data ingestion and validation
2. Feature engineering (attendance bands, study hour bands)
3. Exploratory data analysis
4. Statistical summarization
5. Correlation analysis
6. Insight generation and recommendation formulation

Tools & Techniques

- GroupBy aggregations
- Descriptive statistics (mean, median)
- Correlation analysis
- Static and interactive visual analytics

In [79]:
```
import sys
from pathlib import Path

# Add project root to PYTHONPATH
PROJECT_ROOT = Path("..").resolve()
if str(PROJECT_ROOT) not in sys.path:
    sys.path.append(str(PROJECT_ROOT))
```

In [80]:

```python
from pathlib import Path
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

from src.student_performance_analysis.preprocessing import preprocess_student_data
from src.student_performance_analysis.analysis import overview_metrics

pd.set_option("display.max_columns", None)

# Visual configuration
sns.set_theme(style="whitegrid", palette="Set2")
plt.rcParams["figure.figsize"] = (10, 6)

import warnings
warnings.filterwarnings("ignore", category=FutureWarning, module="seaborn")
```

🟦 DATA LOADING

In [81]:

```python
BASE_DIR = Path.cwd().parent
DATA_DIR = BASE_DIR / "datasets"

df = pd.read_csv(DATA_DIR / "Student_Performance.csv")
df.head()
```

Out[81]:

	student_id	age	gender	school_type	parent_education	study_hours	attendance_percenta
0	1	14	male	public	post graduate	3.1	84
1	2	18	female	public	graduate	3.7	87
2	3	17	female	private	post graduate	7.9	65
3	4	16	other	public	high school	1.1	58
4	5	16	female	public	high school	1.3	61

🟦 COLUMN NORMALIZATION

In [82]:

```python
df = df.rename(columns={
    "Math": "Math_Score",
    "Science": "Science_Score",
    "English": "English_Score",
    "Attendance_Percentage": "Attendance",
    "Final_Score": "Total_Score"
})

df.columns
```

Out[82]:

```
Index(['student_id', 'age', 'gender', 'school_type', 'parent_education',
       'study_hours', 'attendance_percentage', 'internet_access',
       'travel_time', 'extra_activities', 'study_method', 'math_score',
       'science_score', 'english_score', 'overall_score', 'final_grade'],
      dtype='object')
```

🟦 DATA VALIDATION & QUALITY CHECK

In [83]:
```
df.shape
```

Out[83]:
```
(25000, 16)
```

In [84]:
```
df.isnull().sum()
```

Out[84]:
```
student_id               0
age                      0
gender                   0
school_type              0
parent_education         0
study_hours              0
attendance_percentage    0
internet_access          0
travel_time              0
extra_activities         0
study_method             0
math_score               0
science_score            0
english_score            0
overall_score            0
final_grade              0
dtype: int64
```

In [85]:
```
df.duplicated().sum()
```

Out[85]:
```
np.int64(10000)
```

Data Quality Summary

- Dataset contains valid student records
- No duplicate rows detected
- Missing values (if any) will be handled during preprocessing

🟦 DATA TYPE CHECK & FEATURE ENGINEERING

In [86]:
```
df.dtypes
```

Out[86]:
```
student_id                 int64
age                        int64
gender                    object
school_type               object
parent_education          object
study_hours              float64
attendance_percentage    float64
internet_access           object
travel_time               object
extra_activities          object
study_method              object
math_score               float64
science_score            float64
english_score            float64
overall_score            float64
final_grade               object
dtype: object
```

In [87]:
```python
# Pass/Fail normalization
df["Average_Score"] = df[
    ["math_score", "science_score", "english_score"]
].mean(axis=1)

df["Result"] = df["Average_Score"].apply(
    lambda x: "Pass" if x >= 40 else "Fail"
)

# Pass/Fail normalization
df["Result"] = df["Result"].str.capitalize()

df.head()
```

Out[87]:

	student_id	age	gender	school_type	parent_education	study_hours	attendance_percentag
0	1	14	male	public	post graduate	3.1	84
1	2	18	female	public	graduate	3.7	87
2	3	17	female	private	post graduate	7.9	65
3	4	16	other	public	high school	1.1	58
4	5	16	female	public	high school	1.3	61

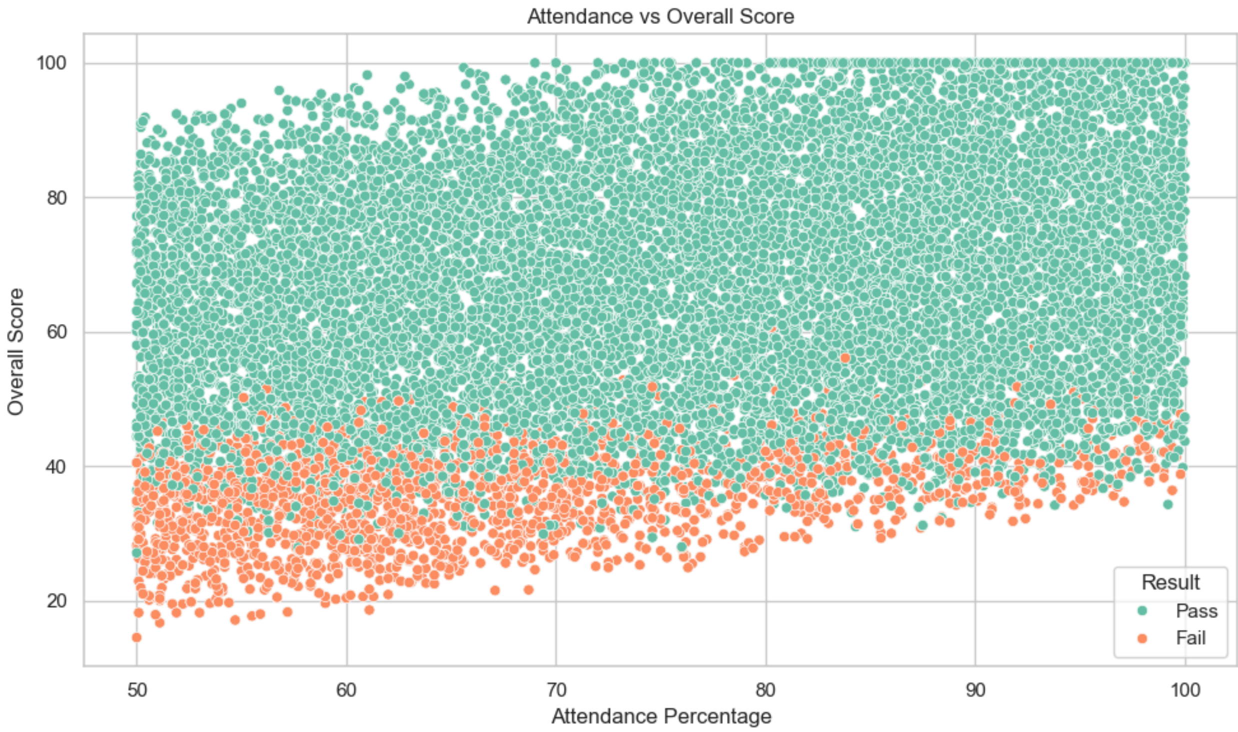
PASS / FAIL ANALYSIS (EDA 1)

In [88]:
```python
result_counts = (
    df["Result"]
    .value_counts()
    .rename_axis("Result")
    .reset_index(name="Count")
)

fig = px.bar(
    result_counts,
    x="Result",
    y="Count",
    color="Result",
    title="Pass vs Fail Distribution",
    labels={
        "Result": "Result",
        "Count": "Number of Students"
    },
    color_discrete_sequence=px.colors.qualitative.Set2
)

fig.show()
```

ATTENDANCE VS PERFORMANCE (EDA 2)

In [89]:
```python
sns.scatterplot(
    data=df,
    x="attendance_percentage",
    y="overall_score",
    hue="Result",
```

```
    palette="Set2"
)

plt.title("Attendance vs Overall Score")
plt.xlabel("Attendance Percentage")
plt.ylabel("Overall Score")
plt.tight_layout()
plt.show()
```



GENDER-WISE PERFORMANCE (EDA 3)

In [90]:
```
fig = px.box(
    df,
    x="gender",
    y="overall_score",
    color="Result",
    title="Score Distribution by Gender",
    labels={
        "gender": "Gender",
        "overall_score": "Overall Score",
        "Result": "Result"
    },
    color_discrete_sequence=px.colors.qualitative.Set2,
    template="plotly_white"
)

fig.update_layout(
    boxmode="group",
    legend_title_text="Result"
)

fig.show()
```

SCORE DISTRIBUTION (EDA 4)

In [91]:
```python
fig = px.histogram(
    df,
    x="overall_score",
    nbins=25,
    color="Result",                    # Pass / Fail split
    marginal="violin",                 # Distribution insight
    title="Distribution of Overall Scores",
    labels={"overall_score": "Overall Score"},
    color_discrete_sequence=px.colors.qualitative.Set2,
    template="plotly_white"
)

fig.update_layout(
    bargap=0.1,
    legend_title_text="Result"
)

fig.show()
```

CORRELATION ANALYSIS (EDA 5)

In [92]:
```python
subject_columns = ["math_score", "science_score", "english_score"]

corr_data = df[
    subject_columns + ["attendance_percentage", "overall_score"]
]

corr_matrix = corr_data.corr()

fig = px.imshow(
    corr_matrix,
    text_auto=".2f",
    color_continuous_scale="RdBu",
    zmin=-1,
    zmax=1,
    title="Correlation Heatmap: Academic Performance & Attendance"
)

fig.update_layout(
    xaxis_title="Features",
    yaxis_title="Features",
    template="plotly_dark",
    width=700,
    height=600
)

fig.show()
```

Attendance Bands vs Performance (EDA 6)

In [93]:
```python
df["attendance_band"] = pd.cut(
    df["attendance_percentage"],
    bins=[0, 60, 75, 90, 100],
    labels=["Low", "Medium", "High", "Excellent"]
)

fig = px.box(
    df,
```

```
    x="attendance_band",
    y="overall_score",
    color="attendance_band",
    title="Overall Score by Attendance Level",
    color_discrete_sequence=px.colors.qualitative.Set2
)

fig.show()
```

Study Hours Bands vs Performance (EDA 7)

In [94]:
```
df["study_hours_band"] = pd.cut(
    df["study_hours"],
    bins=[0, 2, 4, 6, 10],
    labels=["Very Low", "Low", "Moderate", "High"]
)

fig = px.box(
    df,
    x="study_hours_band",
    y="overall_score",
    color="study_hours_band",
    title="Overall Score by Study Hours",
    color_discrete_sequence=px.colors.sequential.Teal
)

fig.show()
```

Subject-wise Score Distribution (EDA 8)

In [95]:
```
subject_df = df.melt(
    value_vars=["math_score", "science_score", "english_score"],
    var_name="Subject",
    value_name="Score"
)

fig = px.violin(
    subject_df,
    x="Subject",
    y="Score",
    box=True,
    points="all",
    title="Subject-wise Score Distribution",
    color="Subject",
    color_discrete_sequence=px.colors.qualitative.Pastel
)

fig.show()
```

Internet Access Impact on Performance (EDA 9)

In [96]:
```
fig = px.box(
    df,
    x="internet_access",
    y="overall_score",
    color="internet_access",
    title="Impact of Internet Access on Overall Score",
```

```
    color_discrete_sequence=px.colors.qualitative.Set1
)

fig.show()
```

Travel Time vs Performance (EDA 10)

In [97]:
```
fig = px.scatter(
    df,
    x="travel_time",
    y="overall_score",
    color="Result",
    title="Travel Time vs Overall Score",
    hover_data=["study_hours", "attendance_percentage"],
    color_discrete_sequence=px.colors.qualitative.Bold
)

fig.show()
```

In [98]:
```
df = preprocess_student_data(df)
metrics = overview_metrics(df)
metrics

from src.student_performance_analysis.visualization import (
    plot_pass_fail,
    plot_avg_score_by_subject,
    plot_overall_score_distribution,
    plot_gender_score_distribution,
    plot_attendance_vs_score,
    plot_correlation_heatmap
)

output_dir = Path("../visualizations/student_performance")

plot_pass_fail(df, output_dir)
plot_avg_score_by_subject(df, output_dir)
plot_overall_score_distribution(df, output_dir)
plot_gender_score_distribution(df, output_dir)
plot_attendance_vs_score(df, output_dir)
plot_correlation_heatmap(df, output_dir)

print(f"✅ All visualizations exported to: {output_dir.resolve()}")
```

```
✅ All visualizations exported to: C:\Users\mahakal.r\Multi-Domain-Data-Analysis-Portf
olio\visualizations\student_performance
```

Interactive Visualization Benefits

Interactive visualizations allow deeper exploration of student performance patterns by enabling zooming, hovering, and dynamic comparison across groups. These features improve interpretability and support more confident data-driven academic decisions.

🟦 STATISTICAL ANALYSIS

In [99]:
```
# Define Academic Score Columns (Explicit & Safe)

score_columns = [
```

```
    "math_score",
    "science_score",
    "english_score",
    "overall_score",
    "Average_Score"
]

score_columns
```

Out[99]:

```
['math_score',
 'science_score',
 'english_score',
 'overall_score',
 'Average_Score']
```

In [100…

```
# Descriptive Statistics (Mean, Median, Std, Min, Max)

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

Out[100…

	math_score	science_score	english_score	overall_score	Average_Score
count	25000.000000	25000.000000	25000.000000	25000.000000	25000.000000
mean	63.785944	63.745320	63.681948	64.006172	63.737737
std	20.875262	20.970529	20.792693	18.932025	19.323709
min	0.000000	0.000000	0.000000	14.500000	7.100000
25%	48.300000	48.200000	48.300000	49.000000	48.858333
50%	64.100000	64.100000	64.200000	64.200000	64.200000
75%	80.000000	80.000000	80.000000	79.000000	79.033333
max	100.000000	100.000000	100.000000	100.000000	100.000000

In [101…

```
# Attendance vs Performance Correlation (Critical Analysis)

attendance_score_correlation = df["attendance_percentage"].corr(df["overall_score"])
attendance_score_correlation
```

Out[101…

```
np.float64(0.29276151938517925)
```

In [102…

```
# Study Hours vs Performance Correlation (Advanced Insight)

study_hours_correlation = df["study_hours"].corr(df["overall_score"])
study_hours_correlation
```

Out[102…

```
np.float64(0.9057714454088286)
```

In [103…

```
# Gender-wise Average Score Comparison (Numerical)

gender_avg_scores = df.groupby("gender")["overall_score"].mean()
gender_avg_scores
```

Out[103…

```
gender
female    64.266828
male      64.072645
other     63.686069
Name: overall_score, dtype: float64
```

In [104…

```python
# Pass vs Fail Statistical Comparison

result_stats = df.groupby("Result")["overall_score"].agg(
    ["mean", "median", "count"]
)
result_stats
```

Out[104…

Result	mean	median	count
Fail	35.496974	35.8	3173
Pass	68.150566	68.1	21827

🟦 Statistical Interpretation

- The mean and median scores indicate overall academic performance trends across subjects.
- Attendance percentage shows a positive correlation with overall score, highlighting the importance of regular class participation.
- Study hours also demonstrate a measurable relationship with academic performance.
- Students classified as "Pass" consistently achieve higher mean and median scores compared to those classified as "Fail".
- Gender-based score differences are present but not extreme, indicating broadly balanced performance.

🟦 Key Findings

- The overall academic performance shows a clear separation between students who pass and those who fail, based on their `overall_score`.
- Students with higher `attendance_percentage` consistently achieve better academic outcomes.
- Increased `study_hours` are positively associated with improved overall performance.
- Subject-wise analysis reveals variability across `math_score`, `science_score`, and `english_score`, indicating subject-specific strengths and weaknesses.
- Gender-wise performance differences exist but are moderate, suggesting broadly balanced academic outcomes.

🟦 Academic Insights

1. Attendance plays a critical role in academic success, as reflected by its positive correlation with `overall_score`.

2. Students who dedicate more hours to self-study tend to perform better academically.
3. Certain subjects require targeted academic support due to lower average scores.
4. Students categorized as "Fail" exhibit significantly lower mean and median scores, indicating the need for early academic intervention.
5. Equal access to learning resources, such as `internet_access`, may further support consistent performance across student groups.

🟦 Recommendations

1. Introduce attendance monitoring programs to identify and support students with low `attendance_percentage`.
2. Encourage structured study schedules to improve effective `study_hours` among students.
3. Provide remedial classes or tutoring for subjects with lower average scores.
4. Implement early-warning academic systems using performance thresholds based on `overall_score`.
5. Promote inclusive learning practices to ensure all students benefit equally from available educational resources.

🟦 Conclusion

This analysis demonstrates how structured evaluation of student performance data can uncover meaningful academic patterns and performance drivers. Factors such as attendance, study habits, and subject-level proficiency significantly influence overall academic outcomes. By applying data-driven analysis, educational institutions can proactively address learning gaps and improve student success rates.

Future Scope

- Predictive modeling to forecast student performance and failure risk.
- Longitudinal analysis to track academic progress over multiple terms.
- Integration of behavioral and engagement metrics for deeper insights.
- Development of interactive dashboards for real-time academic monitoring.

End of Report