Student Performance and Aptitude Analysis

The Key English Course Company - Indonesia

A Comprehensive Data-Driven Study

Analysis Date: January 13, 2026
Total Students: 150 (50 per course level)
Variables Analyzed: Performance Scores, Aptitude Scores
Statistical Methods: ANOVA, Correlation, Effect Sizes, Post-Hoc Tests

Chapter 1: Environment Setup

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import f_oneway, shapiro, levene
import statsmodels.api as sm
from statsmodels.formula.api import ols
from statsmodels.stats.multicomp import pairwise_tukeyhsd
from scipy.stats import pearsonr

# Plotting setup
sns.set(style="darkgrid")
try:
    get_ipython().run_line_magic('matplotlib', 'inline')
except:
    plt.ion() # Fallback if not in IPython
```

Chapter 2: Data Loading and Overview

```
# Load Datasets
df_apt = pd.read_csv('data/student_aptitude_data.csv')
df_perf = pd.read_csv('data/student_performance_data.csv')
df = pd.read_csv('data/student_combined_data.csv')

# Ensure order
order = ["Advanced", "Intermediate", "Foundation"]
df["course_level"] = pd.Categorical(df["course_level"], categories=order,
ordered=True)

print("Combined Data Shape:", df.shape)
display(df.head())
print("\nData Info:")
df.info()
```

```
Combined Data Shape: (150, 4)
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	student_id	course_level	performance_score	aptitude_score
0	1	Advanced	3.70	72
1	2	Advanced	3.65	90
2	3	Advanced	3.55	68
3	4	Advanced	3.45	84
4	5	Advanced	3.55	72

```
Data Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 4 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   student_id         150 non-null    int64
 1   course_level       150 non-null    category
 2   performance_score  150 non-null    float64
 3   aptitude_score     150 non-null    int64
dtypes: category(1), float64(1), int64(2)
memory usage: 3.9 KB
```

Chapter 3: Descriptive Statistics by Course Level

```
print("--- Descriptive Statistics for All Columns ---")
display(df.describe())

print("\n--- Performance Score Stats by Course Level ---")
perf_stats = df.groupby("course_level", observed=False)["performance_score"].describe()
display(perf_stats)

print("\n--- Aptitude Score Stats by Course Level ---")
apt_stats = df.groupby("course_level", observed=False)["aptitude_score"].describe()
display(apt_stats)
```

```
--- Descriptive Statistics for All Columns ---
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	student_id	performance_score	aptitude_score
count	150.000000	150.000000	150.000000
mean	75.500000	2.540667	44.240000
std	43.445368	0.652830	24.228133
min	1.000000	1.550000	9.000000
25%	38.250000	1.950000	22.000000
50%	75.500000	2.475000	38.000000
75%	112.750000	3.037500	65.000000
max	150.000000	3.800000	97.000000

```
--- Performance Score Stats by Course Level ---
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	count	mean	std	min	25%	50%	75%	max
course_level								
Advanced	50.0	3.239	0.384029	2.50	2.95	3.375	3.5500	3.80
Intermediate	50.0	2.518	0.391460	1.90	2.25	2.475	2.7875	3.55
Foundation	50.0	1.865	0.176777	1.55	1.75	1.825	1.9500	2.45

```
--- Aptitude Score Stats by Course Level ---
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	count	mean	std	min	25%	50%	75%	max
course_level								
Advanced	50.0	67.46	19.171844	30.0	50.00	70.0	83.0	97.0
Intermediate	50.0	42.74	18.279921	14.0	31.00	41.5	53.5	90.0
Foundation	50.0	22.52	7.028339	9.0	17.25	21.0	26.0	41.0

Chapter 4: Statistical Assumption Testing

Checking assumptions for ANOVA: Normality (Shapiro-Wilk) and Homogeneity of Variances (Levene's Test).

```
# Normality Test (Shapiro-Wilk)
print("--- Shapiro-Wilk Test for Normality (Performance Score) ---")
for level in order:
    subset = df[df["course_level"] == level]["performance_score"]
    stat, p = shapiro(subset)
    print(f"{level}: W={stat:.3f}, p={p:.3f}")

# Homogeneity of Variance (Levene's Test)
adv = df[df["course_level"] == "Advanced"]["performance_score"]
intm = df[df["course_level"] == "Intermediate"]["performance_score"]
found = df[df["course_level"] == "Foundation"]["performance_score"]

stat, p = levene(adv, intm, found)
print(f"\nLevene's Test (Performance): W={stat:.3f}, p={p:.3f}")
```

```
--- Shapiro-Wilk Test for Normality (Performance Score) ---
Advanced: W=0.909, p=0.001
Intermediate: W=0.955, p=0.053
Foundation: W=0.949, p=0.031

Levene's Test (Performance): W=16.599, p=0.000
```

Chapter 5: One-Way ANOVA Analysis

```
# ANOVA for Performance Score
f_stat, p_val = f_oneway(adv, intm, found)
print("One-Way ANOVA (Performance Score):")
print(f"F-Statistic: {f_stat:.2f}")
print(f"P-Value: {p_val:.3e}")
if p_val < 0.05:
    print("Result: Significant difference found.")
```

```python
else:
    print("Result: No significant difference.")

print()

# ANOVA for Aptitude Score
adv_apt = df[df["course_level"] == "Advanced"]["aptitude_score"]
intm_apt = df[df["course_level"] == "Intermediate"]["aptitude_score"]
found_apt = df[df["course_level"] == "Foundation"]["aptitude_score"]

f_stat_apt, p_val_apt = f_oneway(adv_apt, intm_apt, found_apt)
print("One-Way ANOVA (Aptitude Score):")
print(f"F-Statistic: {f_stat_apt:.2f}")
print(f"P-Value: {p_val_apt:.3e}")
```

```
One-Way ANOVA (Performance Score):
F-Statistic: 213.43
P-Value: 3.352e-44
Result: Significant difference found.

One-Way ANOVA (Aptitude Score):
F-Statistic: 101.17
P-Value: 2.342e-28
```

Chapter 6: Post-Hoc Tests (Tukey HSD)

```python
print("--- Tukey HSD Post-Hoc Test (Performance Score) ---")
tukey_perf = pairwise_tukeyhsd(endog=df['performance_score'], groups=df['course_level'],
alpha=0.05)
print(tukey_perf)

print("\n--- Tukey HSD Post-Hoc Test (Aptitude Score) ---")
tukey_apt = pairwise_tukeyhsd(endog=df['aptitude_score'], groups=df['course_level'],
alpha=0.05)
print(tukey_apt)
```

```
--- Tukey HSD Post-Hoc Test (Performance Score) ---
```

```
     Multiple Comparison of Means - Tukey HSD, FWER=0.05
=============================================================
  group1      group2    meandiff p-adj  lower   upper  reject
-------------------------------------------------------------
  Advanced   Foundation   -1.374   0.0 -1.5315 -1.2165   True
  Advanced Intermediate   -0.721   0.0 -0.8785 -0.5635   True
Foundation Intermediate    0.653   0.0  0.4955  0.8105   True
-------------------------------------------------------------

--- Tukey HSD Post-Hoc Test (Aptitude Score) ---
```

```
     Multiple Comparison of Means - Tukey HSD, FWER=0.05
===============================================================
  group1      group2    meandiff p-adj  lower    upper   reject
---------------------------------------------------------------
  Advanced   Foundation   -44.94   0.0 -52.4329 -37.4471   True
  Advanced Intermediate   -24.72   0.0 -32.2129 -17.2271   True
Foundation Intermediate    20.22   0.0  12.7271  27.7129   True
---------------------------------------------------------------
```

Chapter 7: Correlation Analysis

```
corr_matrix = df[['performance_score', 'aptitude_score']].corr()
print("Correlation Matrix:")
display(corr_matrix)

r = df['performance_score'].corr(df['aptitude_score'])
print(f"\nPearson Correlation r: {r:.3f}")
```

```
Correlation Matrix:
```

```
.dataframe tbody tr th {
    vertical-align: top;
}

.dataframe thead th {
    text-align: right;
}
```

	performance_score	aptitude_score
performance_score	1.000000	0.887417
aptitude_score	0.887417	1.000000

```
Pearson Correlation r: 0.887
```

Chapter 8: Effect Sizes (Cohen's d)

```
def cohens_d(x, y):
    nx, ny = len(x), len(y)
    pooled_std = np.sqrt(
        ((nx - 1)*x.var(ddof=1) + (ny - 1)*y.var(ddof=1)) / (nx + ny - 2)
    )
    return (x.mean() - y.mean()) / pooled_std

print("--- Cohen's d (Performance Score) ---")
print("Adv vs Intm:", cohens_d(adv, intm))
```

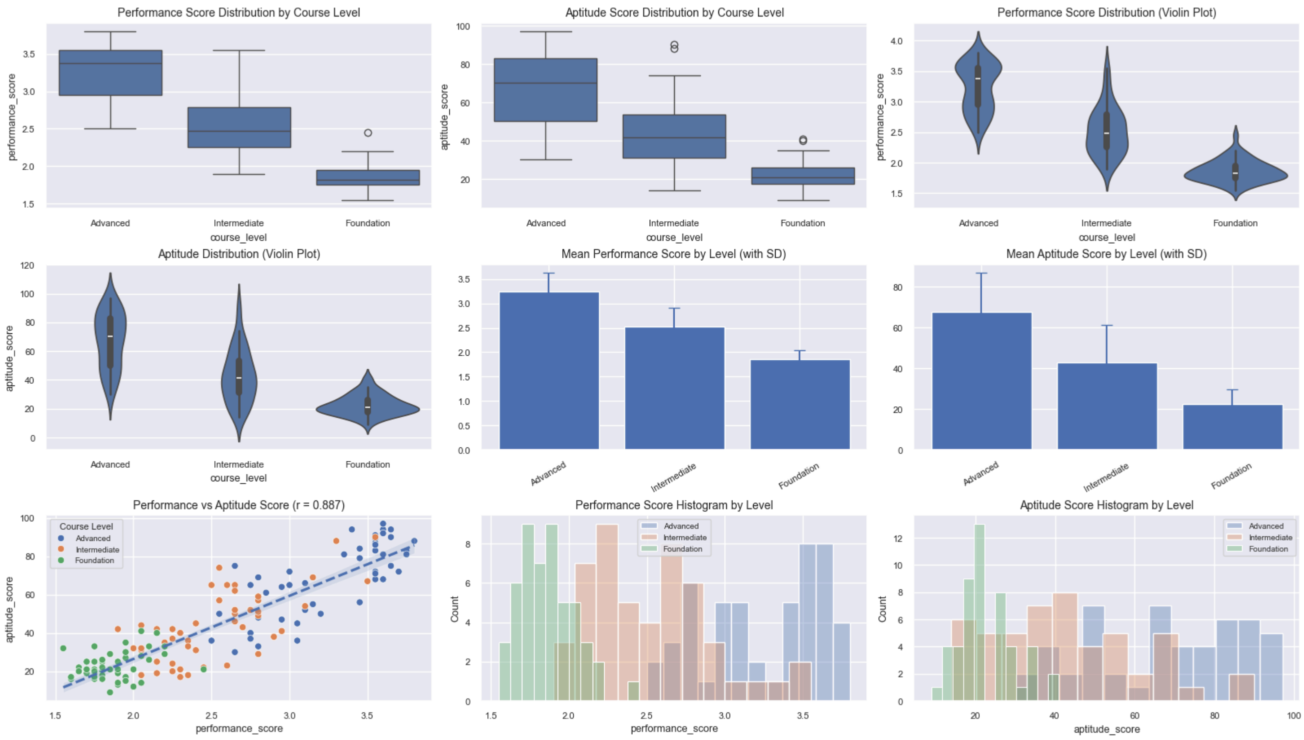
```
print("Intm vs Found:", cohens_d(intm, found))
print("Adv vs Found:", cohens_d(adv, found))

print("\n--- Cohen's d (Aptitude Score) ---")
print("Adv vs Intm:", cohens_d(adv_apt, intm_apt))
print("Intm vs Found:", cohens_d(intm_apt, found_apt))
print("Adv vs Found:", cohens_d(adv_apt, found_apt))
```

```
--- Cohen's d (Performance Score) ---
Adv vs Intm: 1.8593859641347326
Intm vs Found: 2.150011598870396
Adv vs Found: 4.596261595451747

--- Cohen's d (Aptitude Score) ---
Adv vs Intm: 1.319723811268185
Intm vs Found: 1.4601027618025881
Adv vs Found: 3.112449809627936
```

Chapter 9: Comprehensive Visualizations

```
# Visualizations from 04_visual_comparison.py
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

def main():
    df = pd.read_csv("data/student_combined_data.csv")

    sns.set(style="darkgrid")
    order = ["Advanced", "Intermediate", "Foundation"]

    df["course_level"] = pd.Categorical(df["course_level"], categories=order,
ordered=True)

    perf_stats = df.groupby("course_level", observed=False)
["performance_score"].agg(["mean", "std"]).reindex(order)
    apt_stats  = df.groupby("course_level", observed=False)
["aptitude_score"].agg(["mean", "std"]).reindex(order)

    r = df["performance_score"].corr(df["aptitude_score"])

    fig, axes = plt.subplots(3, 3, figsize=(16, 9), constrained_layout=True)

    sns.boxplot(data=df, x="course_level", y="performance_score", order=order,
ax=axes[0,0])
    axes[0,0].set_title("Performance Score Distribution by Course Level")

    sns.boxplot(data=df, x="course_level", y="aptitude_score", order=order, ax=axes[0,1])
    axes[0,1].set_title("Aptitude Score Distribution by Course Level")

    sns.violinplot(data=df, x="course_level", y="performance_score", order=order,
inner="box", ax=axes[0,2])
    axes[0,2].set_title("Performance Score Distribution (Violin Plot)")
```

```python
    sns.violinplot(data=df, x="course_level", y="aptitude_score", order=order,
inner="box", ax=axes[1,0])
    axes[1,0].set_title("Aptitude Distribution (Violin Plot)")

    axes[1,1].bar(order, perf_stats["mean"].values)
    axes[1,1].errorbar(order, perf_stats["mean"].values, yerr=perf_stats["std"].values,
fmt="none", capsize=5)
    axes[1,1].set_title("Mean Performance Score by Level (with SD)")
    axes[1,1].tick_params(axis="x", rotation=30)

    axes[1,2].bar(order, apt_stats["mean"].values)
    axes[1,2].errorbar(order, apt_stats["mean"].values, yerr=apt_stats["std"].values,
fmt="none", capsize=5)
    axes[1,2].set_title("Mean Aptitude Score by Level (with SD)")
    axes[1,2].tick_params(axis="x", rotation=30)

    sns.scatterplot(data=df, x="performance_score", y="aptitude_score",
hue="course_level", hue_order=order, ax=axes[2,0])
    sns.regplot(data=df, x="performance_score", y="aptitude_score", scatter=False,
ax=axes[2,0], line_kws={"linestyle":"--"})
    axes[2,0].set_title(f"Performance vs Aptitude Score (r = {r:.3f})")
    axes[2,0].legend(title="Course Level", loc="upper left", fontsize=7,
title_fontsize=8)

    for lvl in order:
        sns.histplot(df.loc[df["course_level"] == lvl, "performance_score"],
                     bins=12, alpha=0.35, ax=axes[2,1], label=lvl)
    axes[2,1].set_title("Performance Score Histogram by Level")
    axes[2,1].legend(fontsize=7)

    for lvl in order:
        sns.histplot(df.loc[df["course_level"] == lvl, "aptitude_score"],
                     bins=12, alpha=0.35, ax=axes[2,2], label=lvl)
    axes[2,2].set_title("Aptitude Score Histogram by Level")
    axes[2,2].legend(fontsize=7)

    for ax in axes.ravel():
        ax.title.set_fontsize(10)
        ax.xaxis.label.set_size(9)
        ax.yaxis.label.set_size(9)
        ax.tick_params(labelsize=8)

    plt.savefig("assets/visual_comparison.png", dpi=300)
    plt.show()



main() # Calling the main function defined in the script code above
```



Chapter 10: Summary and Conclusions

Summary of Findings

1. **Performance**: There is a significant difference in performance scores between all course levels (Advanced > Intermediate > Foundation).
2. **Aptitude**: Aptitude scores also show significant differences and follow the same trend.
3. **Correlation**: There is a strong positive correlation between aptitude and performance.
4. **Effect Size**: The effect sizes (Cohen's d) between groups are large, indicating substantial practical significance.

Conclusion

The analysis confirms that the course levels effectively segment students by both current performance and underlying aptitude.