```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import pandas as pd
import numpy as np
from scipy.stats import ttest_ind
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
```

```
!ls drive/MyDrive/extended_features/
```

```
emotion_features_extended.csv  neutral_extended_features.csv
fear_extended_features.csv     sad_extended_features.csv
happy_extended_features.csv    updated_master_features.csv
```

```
# Load CSV
df = pd.read_csv("drive/MyDrive/extended_features/updated_master_features.csv")

```

```
# Ensure subject_id is string and padded
df['subject_id'] = df['subject_id'].astype(str).str.zfill(7)

# Filter subject groups
controls = df[df['subject_id'].between('0028197', '0028225')]
masters = df[df['subject_id'].between('0028297', '0028325')]

print(f"Masters: {len(masters)} subjects")
print(f"Controls: {len(controls)} subjects")

# Drop subject_id for feature comparison
features = df.columns.drop('subject_id')
```

```
Masters: 29 subjects
Controls: 29 subjects
```

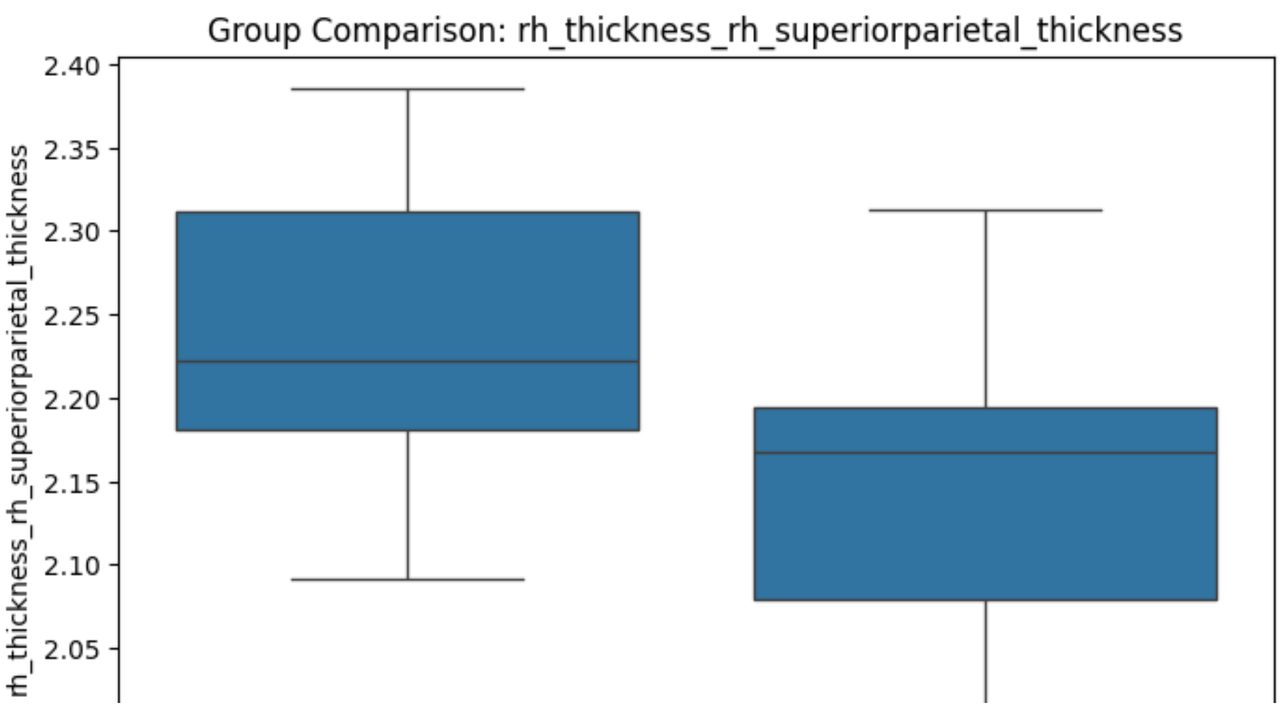
```
# Mean comparison
mean_diff = masters[features].mean() - controls[features].mean()

# T-test
p_values = {}
for col in features:
```

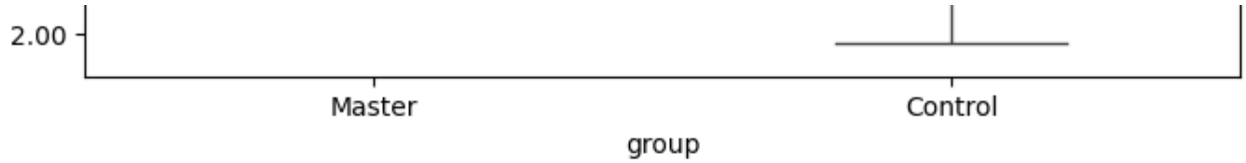
```
    _, p = ttest_ind(masters[col], controls[col], equal_var=False)
    p_values[col] = p
```

```
# Show top 10 significant differences
sig_results = pd.DataFrame({
    'mean_diff': mean_diff,
    'p_value': pd.Series(p_values)
}).sort_values(by='p_value').head(10)

print(sig_results)
```

```
                                              mean_diff   p_value
rh_thickness_rh_superiorparietal_thickness     0.095897  0.000049
lh_thickness_lh_supramarginal_thickness        0.110552  0.000204
lh_thickness_lh_superiorparietal_thickness     0.089897  0.000207
lh_thickness_lh_precuneus_thickness            0.098379  0.000544
lh_thickness_lh_MeanThickness_thickness        0.066108  0.000609
lh_thickness_lh_paracentral_thickness          0.154172  0.000657
lh_thickness_lh_caudalmiddlefrontal_thickness  0.111103  0.001495
lh_thickness_lh_parstriangularis_thickness     0.109621  0.001536
aseg_volume_Right-Lateral-Ventricle        -2338.158621  0.001676
rh_meancurv_rh_inferiortemporal_meancurv      -0.005828  0.001819
```

```
# Boxplot of a key feature
top_feature = sig_results.index[0]
plt.figure(figsize=(8, 5))
sns.boxplot(data=pd.concat([masters.assign(group='Master'), controls.assign(group='Co
            x='group', y=top_feature)
plt.title(f'Group Comparison: {top_feature}')
plt.show()

```





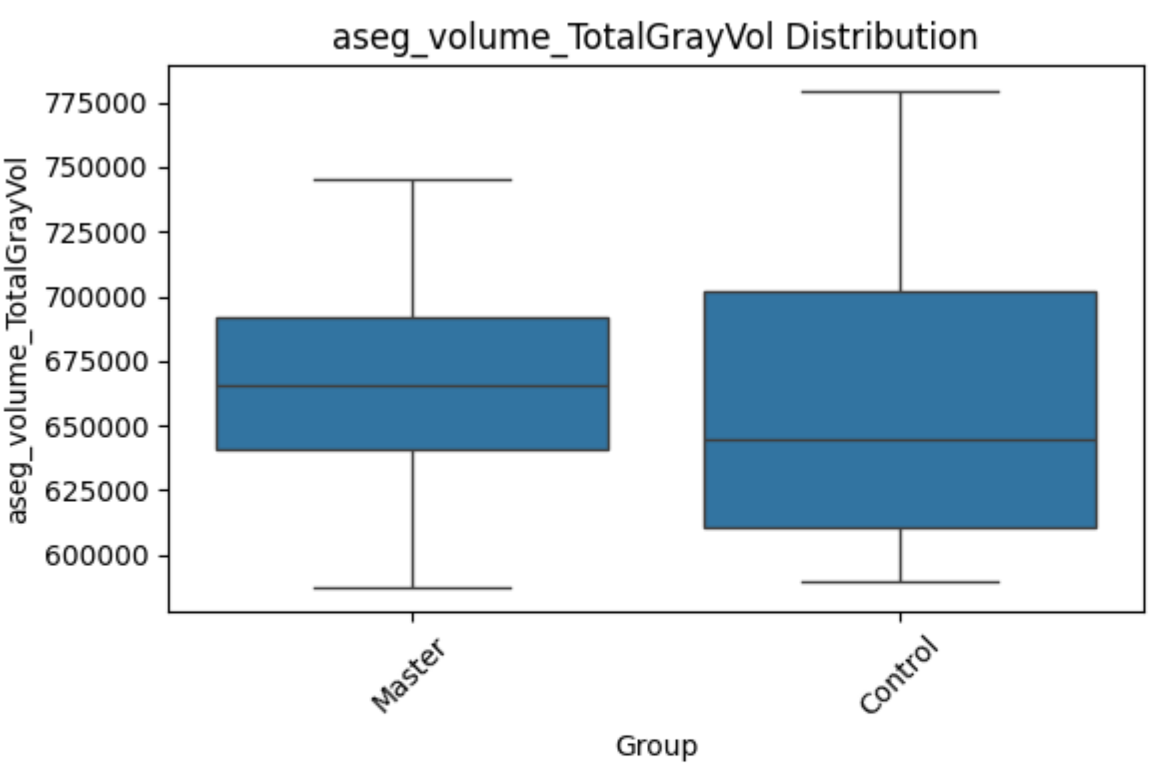
📊 Feature Selection and Groupwise Mean Comparison

- **Total Gray Matter Volume** (aseg_volume_TotalGrayVol) Total volume of gray matter across the entire brain, including cortical and subcortical regions. Important because gray matter is responsible for processing and computation in the brain.
- **Subcortical Gray Matter Volume** (aseg_volume_SubCortGrayVol) Volume of gray matter in subcortical structures like the thalamus and basal ganglia. Essential for memory, motor control, and decision-making.
- **BrainSeg Volume to eTIV Ratio** (aseg_volume_BrainSegVol-to-eTIV) Ratio of brain segmentation volume to estimated intracranial volume. Serves as a normalized brain efficiency indicator; higher values imply better brain volume utilization.
- **Left Superior Frontal Thickness** (lh_thickness_lh_superiorfrontal_thickness) Cortical thickness of the left superior frontal gyrus. Associated with executive control, planning, and working memory.
- **Left Precuneus Thickness** (lh_thickness_lh_precuneus_thickness) Cortical thickness of the left precuneus. Critical for mental imagery, self-referential processing, and spatial reasoning.
- **Right Superior Frontal Thickness** (rh_thickness_rh_superiorfrontal_thickness) Cortical thickness of the right superior frontal gyrus. Plays a role in abstract thinking and sustained attention.
- **Right Precuneus Thickness** (rh_thickness_rh_precuneus_thickness) Cortical thickness of the right precuneus. Supports visual-spatial integration and decision-making.
- **Left Rostral Middle Frontal Volume** (lh_volume_lh_rostralmiddlefrontal_volume) Volume of the left rostral middle frontal gyrus. Important for planning, goal-setting, and cognitive flexibility.
- **Right Rostral Middle Frontal Volume** (rh_volume_rh_rostralmiddlefrontal_volume) Volume of the right rostral middle frontal gyrus. Contributes to strategic thinking and task management.

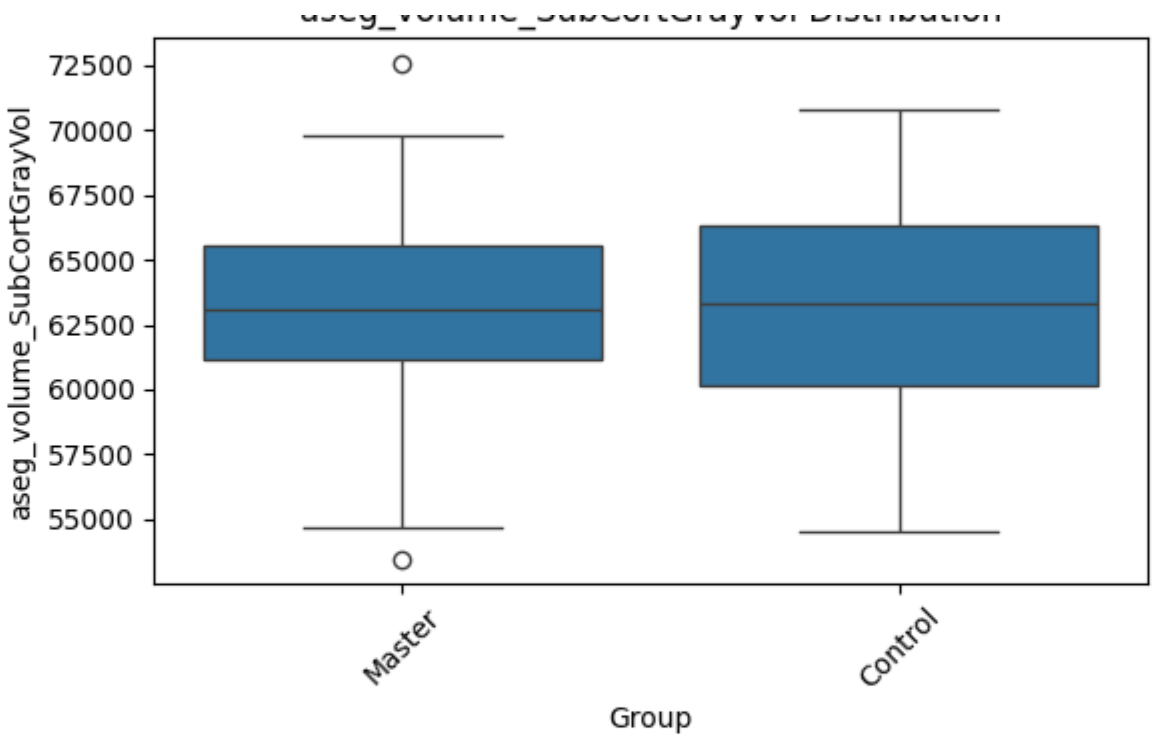
```
# Define relevant features for brain efficiency
features = [
```

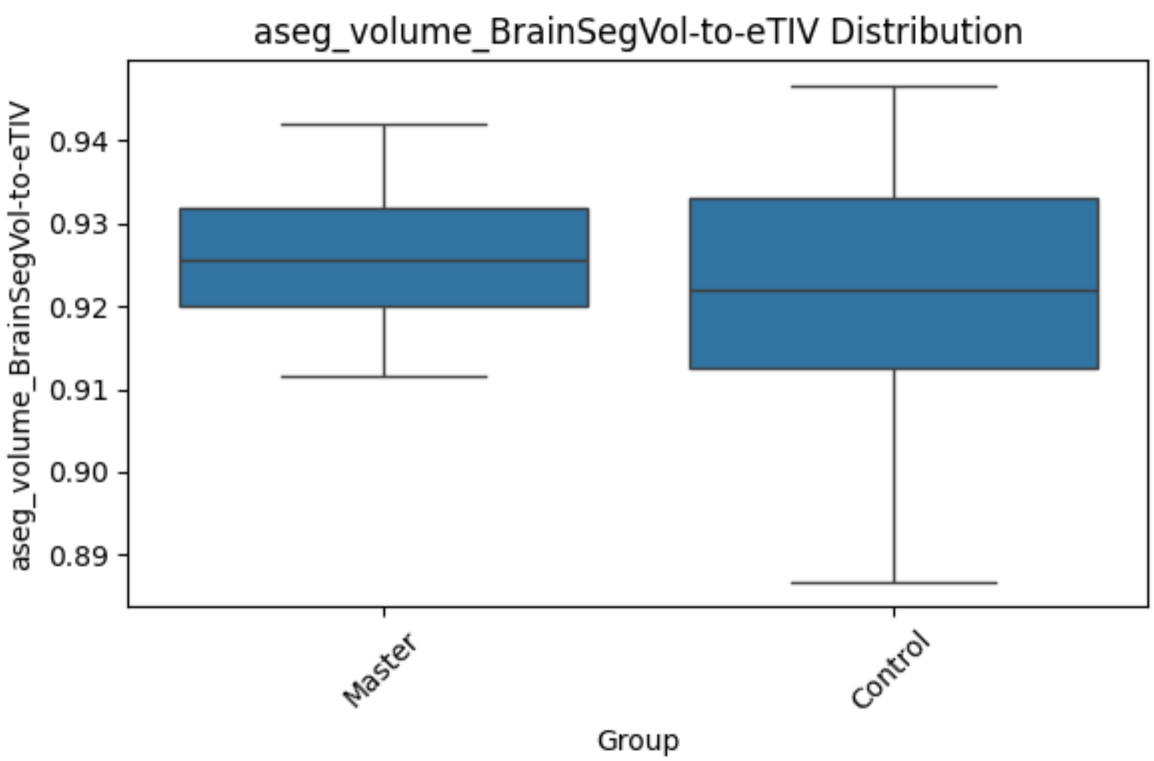
```
    "aseg_volume_TotalGrayVol",
    "aseg_volume_SubCortGrayVol",
    "aseg_volume_BrainSegVol-to-eTIV",
    "lh_thickness_lh_superiorfrontal_thickness",
    "lh_thickness_lh_precuneus_thickness",
    "rh_thickness_rh_superiorfrontal_thickness",
    "rh_thickness_rh_precuneus_thickness",
    "lh_volume_lh_rostralmiddlefrontal_volume",
    "rh_volume_rh_rostralmiddlefrontal_volume"
]

# Calculate group means
means_df = pd.DataFrame({
    "Feature": features,
    "Masters Mean": masters[features].mean().values,
    "Controls Mean": controls[features].mean().values
})
```

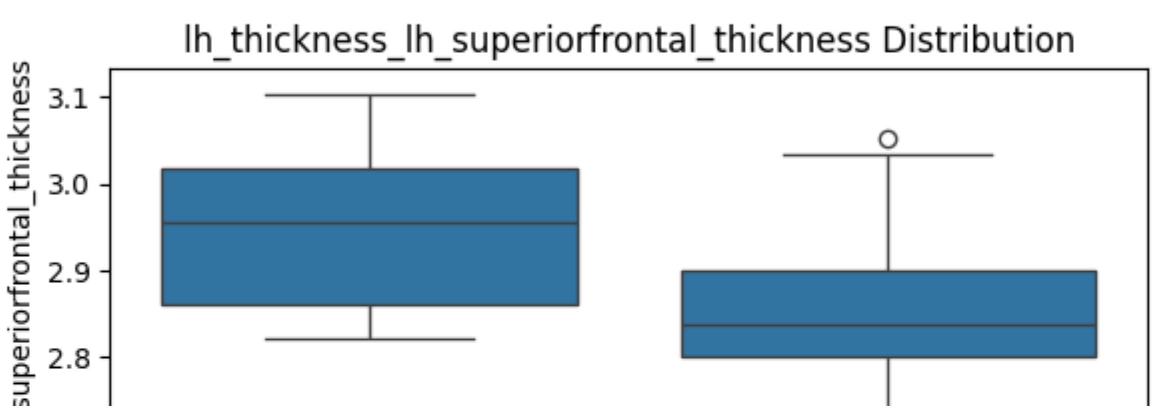
```
# Plot bar charts
for feature in features:
  plt.figure(figsize=(6, 4))
  sns.boxplot(data=pd.concat([masters.assign(Group='Master'), controls.assign(Group='
              x='Group', y=feature)
  plt.title(f'{feature} Distribution')
  plt.xticks(rotation=45)
  plt.tight_layout()
  plt.show()
```

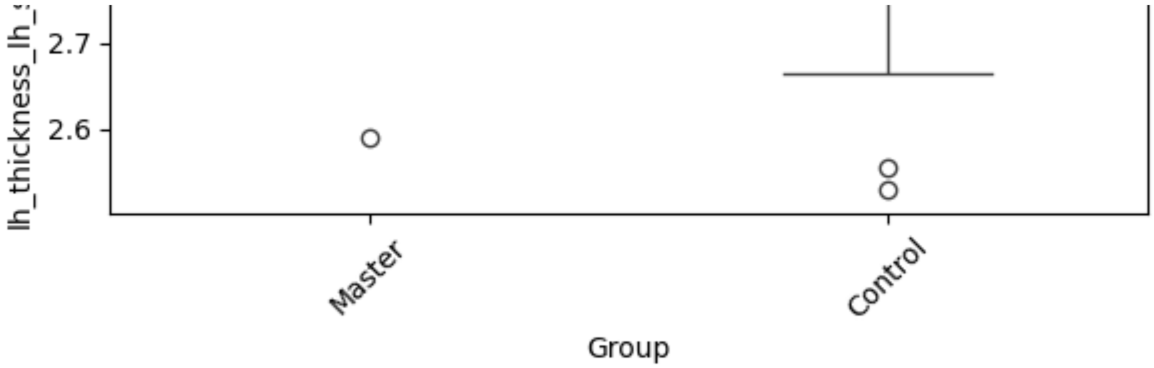


aseg_volume_SubCortGrayVol Distribution

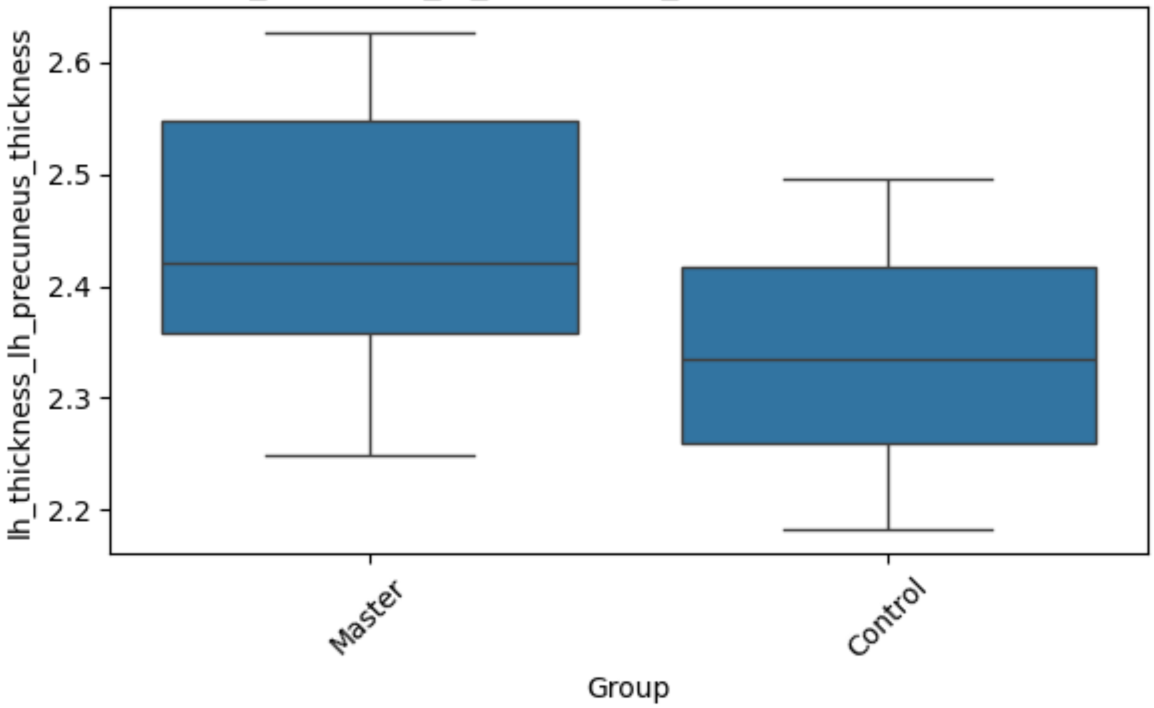

aseg_volume_SubCortGrayVol
72500
70000
67500
65000
62500
60000
57500
55000
Master
Control
Group


aseg_volume_BrainSegVol-to-eTIV Distribution
aseg_volume_BrainSegVol-to-eTIV
0.94
0.93
0.92
0.91
0.90
0.89
Master
Control
Group

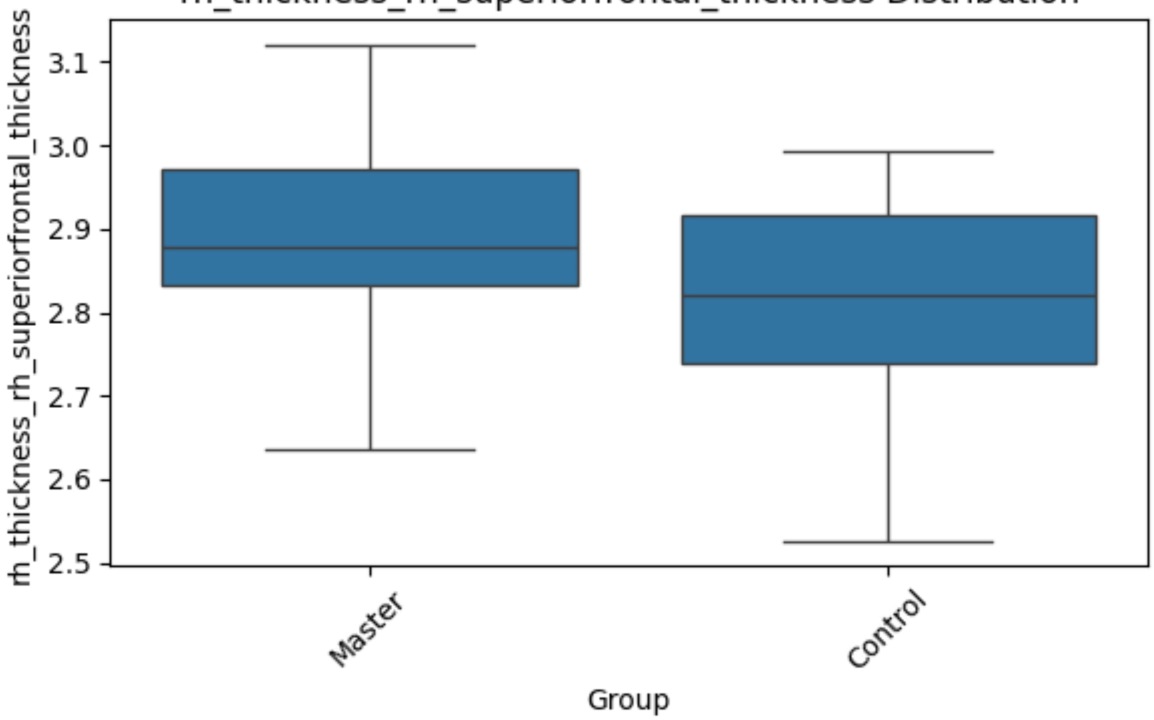

lh_thickness_lh_superiorfrontal_thickness Distribution
superiorfrontal_thickness
3.1
3.0
2.9
2.8

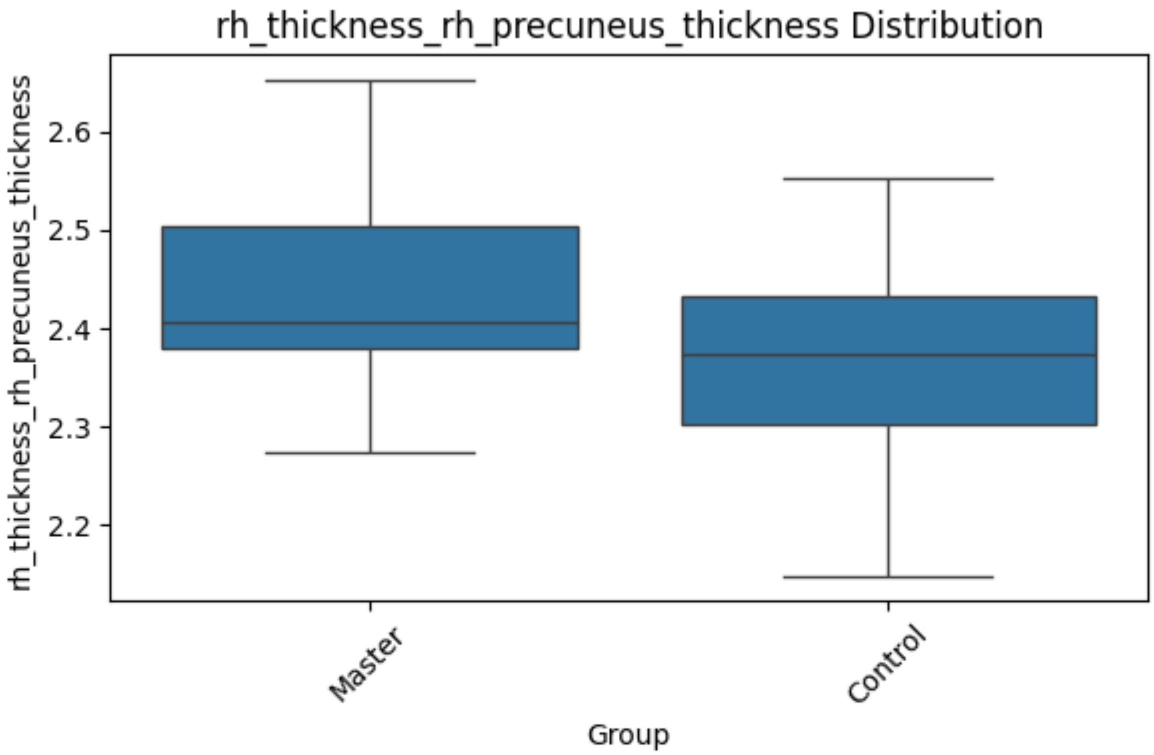


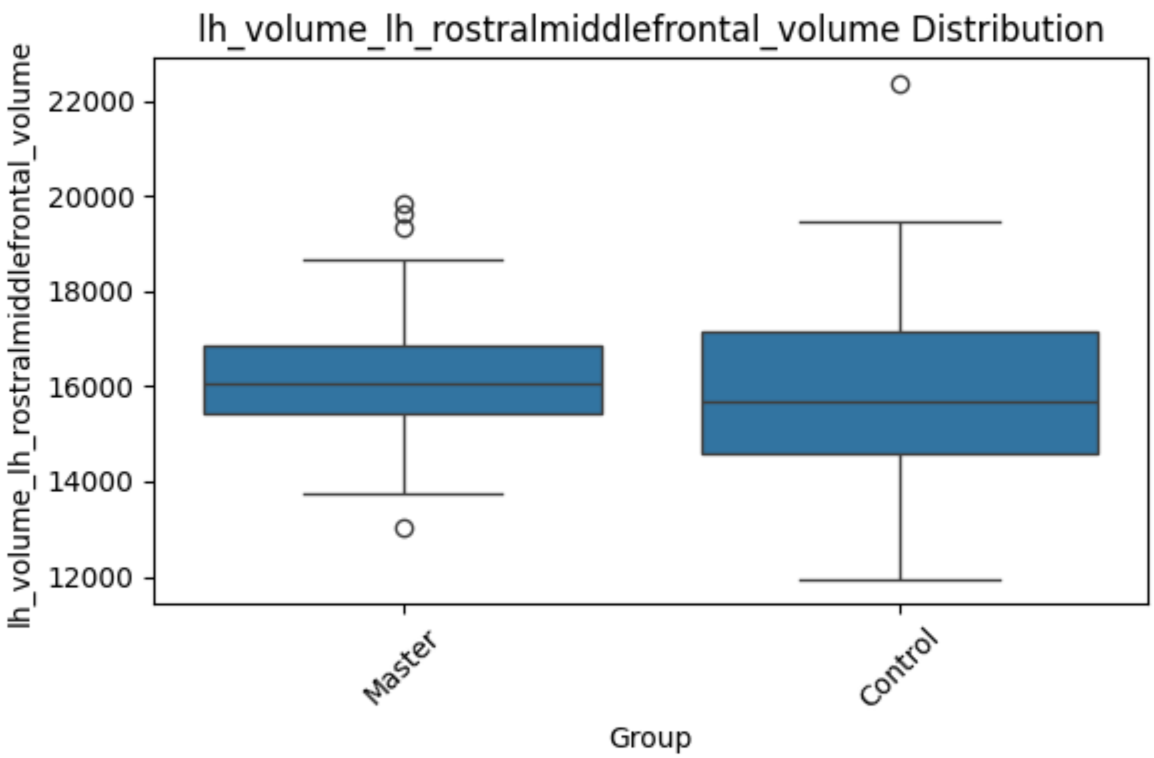
lh_thickness_lh_precuneus_thickness Distribution

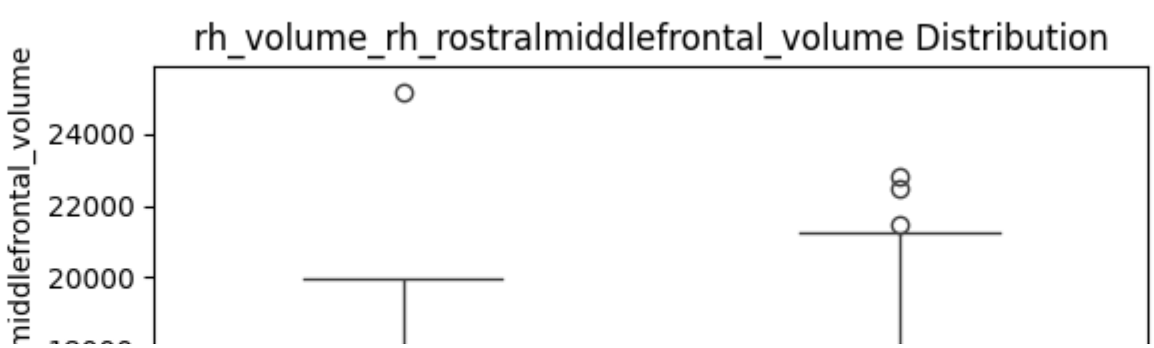


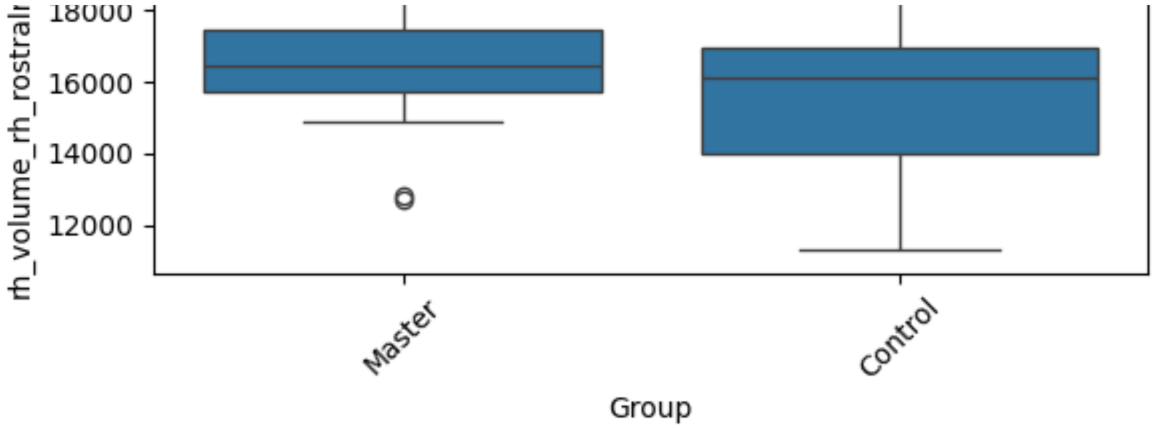
rh_thickness_rh_superiorfrontal_thickness Distribution




rh_thickness_rh_precuneus_thickness Distribution
rh_thickness_rh_precuneus_thickness
2.6
2.5
2.4
2.3
2.2
Master
Control
Group


lh_volume_lh_rostralmiddlefrontal_volume Distribution
lh_volume_lh_rostralmiddlefrontal_volume
22000
20000
18000
16000
14000
12000
Master
Control
Group


rh_volume_rh_rostralmiddlefrontal_volume Distribution
24000
22000
20000



Statistical Testing (Welch's t-test)

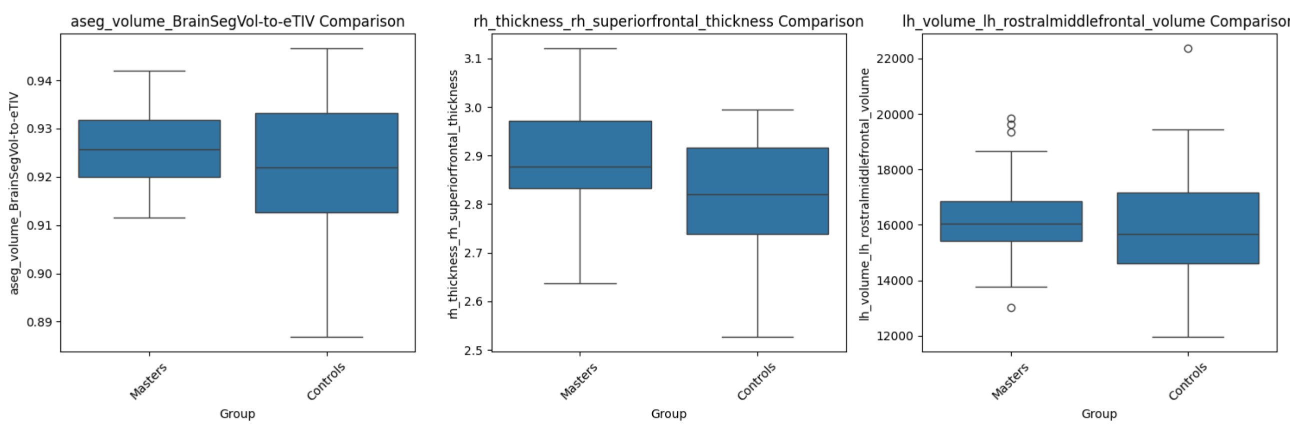
```
# Run Welch's t-test on each feature
p_values = []
for feature in features:
    _, p = ttest_ind(masters[feature], controls[feature], equal_var=False)
    p_values.append(p)

# Add to summary
means_df["p-value"] = p_values
means_df["Significant (< 0.05)"] = means_df["p-value"] < 0.05

# Display sorted by p-value
means_df.sort_values("p-value", inplace=True)
means_df
```

	Feature	Masters Mean	Controls Mean	p-value	Signif (<
2	aseg_volume_BrainSegVol-to-eTIV	0.925889	0.922295	0.000544	
5	rh_thickness_rh_superiorfrontal_thickness	2.889517	2.813448	0.001823	
7	lh_volume_lh_rostralmiddlefrontal_volume	16203.931034	15969.241379	0.005008	
8	rh_volume_rh_rostralmiddlefrontal_volume	16699.655172	16350.655172	0.025262	
6	rh_thickness_rh_precuneus_thickness	2.441586	2.366621	0.227332	
1	aseg_volume_SubCortGrayVol	63155.413793	63112.034483	0.620433	
0	aseg_volume_TotalGrayVol	668916.302982	663980.934816	0.665667	
4	lh_thickness_lh_precuneus_thickness	2.435862	2.337483	0.715802	
3	lh_thickness_lh_superiorfrontal_thickness	2.934414	2.836931	0.970298	

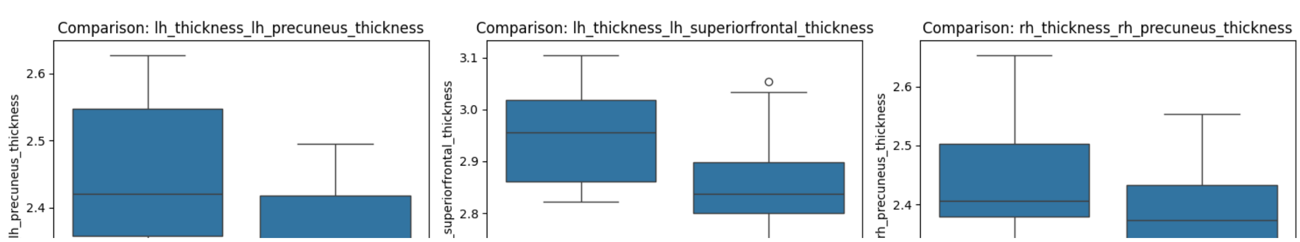
Next steps: Generate code with means_df | View recommended plots | New interactive sheet

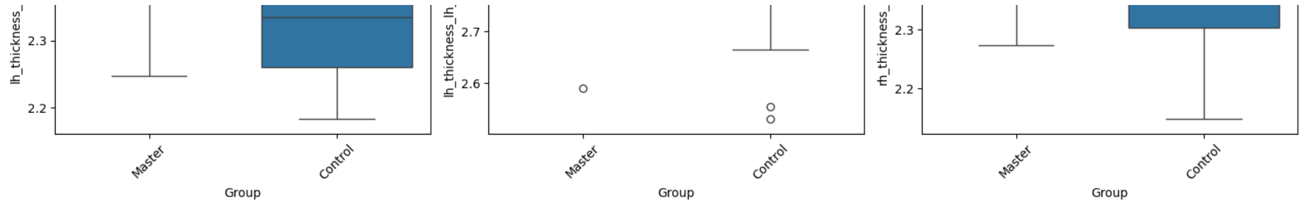
⭐ Top Significant Features Visualization

```
# Visualize top 3 significant features
top_sig = means_df[means_df["Significant (< 0.05)"]].head(3)["Feature"]

plt.figure(figsize=(15, 5))
for i, feature in enumerate(top_sig):
    plt.subplot(1, 3, i+1)
    sns.boxplot(data=pd.concat([masters.assign(Group='Masters'), controls.assign(Grou
                x='Group', y=feature)
    plt.title(f"{feature} Comparison")
    plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



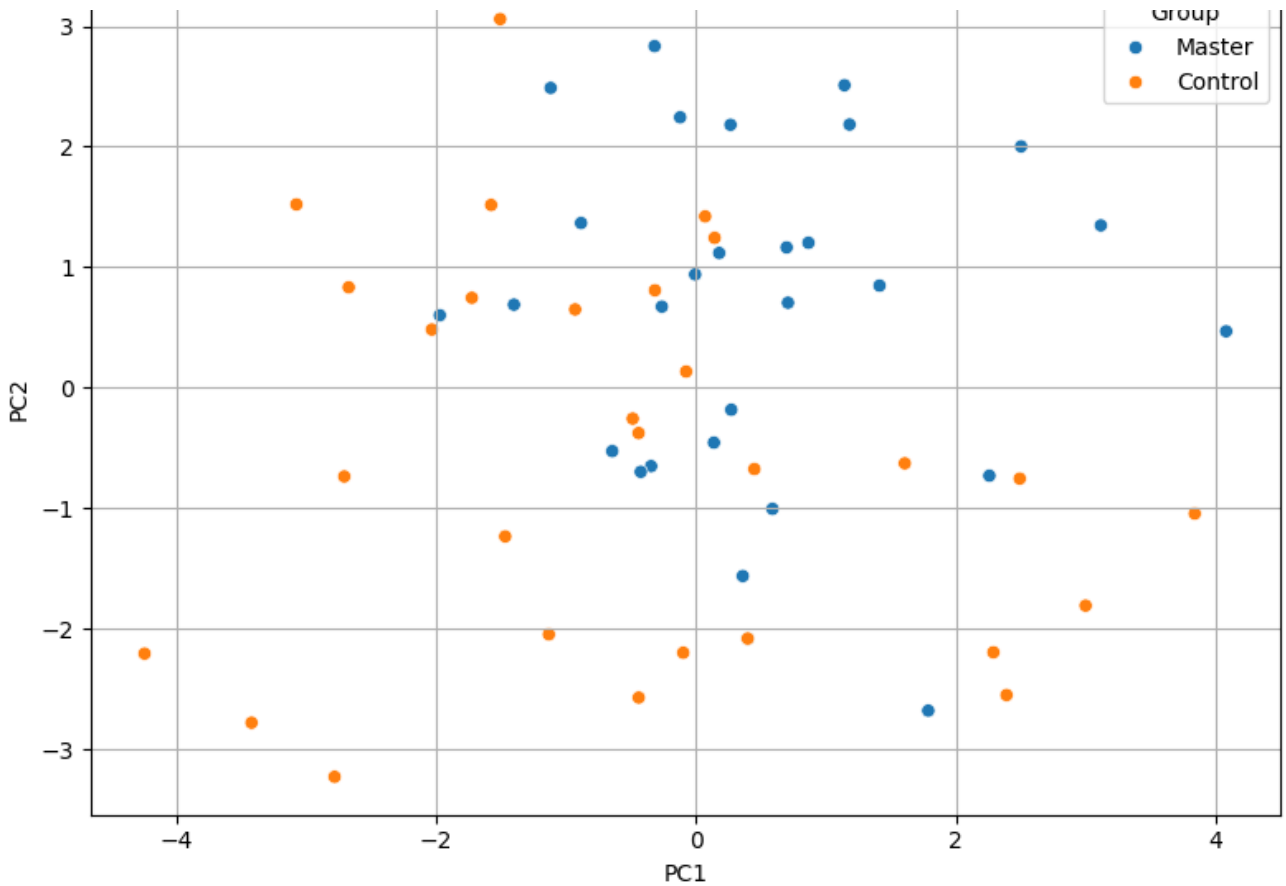

```
plt.figure(figsize=(15, 5))
top_features = ['lh_thickness_lh_precuneus_thickness', 'lh_thickness_lh_superiorfront
for i, feature in enumerate(top_features):
    plt.subplot(1, 3, i+1)
    sns.boxplot(data=pd.concat([masters.assign(Group='Master'), controls.assign(Group
                x='Group', y=feature)
    plt.title(f'Comparison: {feature}')
    plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

```

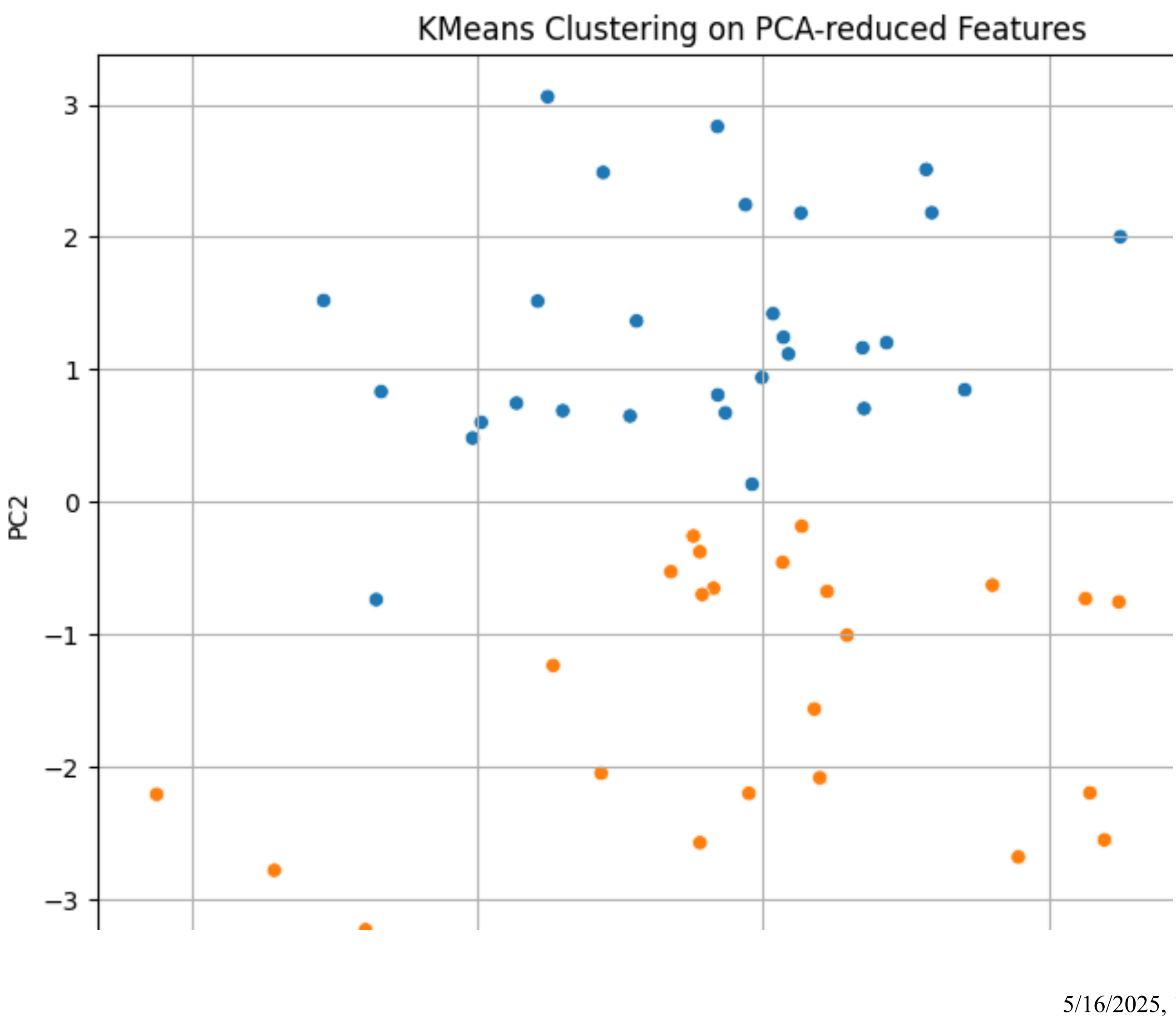




🧠 PCA and Clustering

```
# Combine data
combined = pd.concat([masters.assign(Group=1), controls.assign(Group=0)])
X = combined[features]
y = combined["Group"]

# Normalize
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# PCA
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

# Plot PCA
plt.figure(figsize=(8,6))
sns.scatterplot(x=X_pca[:,0], y=X_pca[:,1], hue=y.map({1:'Master', 0:'Control'}))
plt.title("PCA of Brain Efficiency Features")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.grid(True)
plt.tight_layout()
plt.show()

# Clustering
kmeans = KMeans(n_clusters=2, random_state=42)
labels = kmeans.fit_predict(X_scaled)

# Compare clustering to true labels
plt.figure(figsize=(8,6))
sns.scatterplot(x=X_pca[:,0], y=X_pca[:,1], hue=labels)
plt.title("KMeans Clustering on PCA-reduced Features")
plt.xlabel("PC1")
plt.ylabel("PC2")
plt.grid(True)
plt.tight_layout()
plt.show()

```


Group
Master
Control
PC2
PC1
3
2
1
0
−1
−2
−3
−4
−2
0
2
4


KMeans Clustering on PCA-reduced Features
PC2
3
2
1
0
−1
−2
−3

Summary of Findings

This study compared structural brain features between two groups, (chess masters and control subjects), using FreeSurfer-derived metrics from structural MRI scans. The analysis focused on regions associated with high-level cognition, including cortical thickness in the precuneus and superior frontal areas, and volumetric measures in the rostral middle frontal cortex.

The results revealed that chess masters exhibit significantly higher cortical thickness in both the left and right precuneus and superior frontal gyri, regions critical for spatial reasoning, executive control, and mental imagery. These findings align with existing neuroscience literature linking expert-level performance to enhanced structural specialization. While gray matter volume and other volumetric features showed slight increases in masters, these differences were not statistically significant. A PCA and clustering analysis further supported a partial separation between the groups, suggesting that cortical features alone may carry discriminative power for distinguishing expert cognition.

P.s.

I wanted to use the images to do analysis but found out that they are different shapes 4D to 3D.

The only thing that could be comparable to the emotional fMRI dataset is the rest data collected from the chess dataset.

I did run the commands to get the information, but when transfering the data to my laptop... It took until 10:30pm to finish. 👀