```
# Technique: Create 'Avg_Grade' and 'Total_Approved'
# Justification: Semester-specific data (e.g., grades, approved units) lacks hc
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from google.colab import drive
import os

# Mount Google Drive
drive.mount('/content/drive')
Mounted at /content/drive
```

```
# Define paths and create directories
data_path = '/content/drive/My Drive/rawDataset.csv'
results_path = '/content/drive/My Drive/results/'
eda_vis_path = results_path + 'eda_visualizations/'
os.makedirs(eda_vis_path, exist_ok=True)
```

```
# Feature Engineering: Creation of Aggregated Features
df['Avg_Grade'] = (df['Curricular units 1st sem (grade)'] + df['Curricular unit
df['Total_Approved'] = df['Curricular units 1st sem (approved)'] + df['Curricular units 1st sem (approved)']
```

```
# Handle missing or invalid values (e.g., NaN or infinite values from division)
df['Avg_Grade'] = df['Avg_Grade'].replace([np.inf, -np.inf], np.nan).fillna(0)
df['Total_Approved'] = df['Total_Approved'].fillna(0)
```

```
# Feature Engineering: Dimension Reduction using PCA on Curricular Units Featur
# Select relevant features for PCA (focusing on curricular units to reduce dime
curricular_features = [
    'Curricular units 1st sem (credited)', 'Curricular units 1st sem (enrolled)
```

0

1

3

-5.436567

0.085205

-3.589884

0.325992

df.to_csv(processed_path, index=False)

```
'Curricular units 1st sem (evaluations)', 'Curricular units 1st sem (approv
'Curricular units 1st sem (grade)', 'Curricular units 1st sem (without eval
'Curricular units 2nd sem (credited)', 'Curricular units 2nd sem (enrolled)
'Curricular units 2nd sem (evaluations)', 'Curricular units 2nd sem (approv
'Curricular units 2nd sem (grade)', 'Curricular units 2nd sem (without eval]

X = df[curricular_features]
```

```
# Standardize the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply PCA to reduce to 2 components for visualization and efficiency
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

# Add PCA components back to dataframe
df['PCA_Component1'] = X_pca[:, 0]
df['PCA_Component2'] = X_pca[:, 1]

print("\nPCA Explained Variance Ratio:", pca.explained_variance_ratio_)
print("PCA Components Sample:\n", df[['PCA_Component1', 'PCA_Component2']].heac

PCA Explained Variance Ratio: [0.51379728 0.16979443]
PCA Components Sample:
    PCA Component1 PCA Component2
```

```
# Save the processed dataset (for group pipeline integration)
processed_path = results_path + 'outputs/member5_processed_features.csv'
# Create the directory if it doesn't exist
os.makedirs(os.path.dirname(processed_path), exist_ok=True)
```

Processed features saved to: /content/drive/My Drive/results/outputs/member5_pro

```
# EDA Visualization: Scatterplot of PCA Components colored by Target
plt.figure(figsize=(8, 6))
sns.scatterplot(x='PCA_Component1', y='PCA_Component2', hue='Target', data=df)
plt.title("PCA Components by Target (Dimension Reduction Visualization)")
plt.savefig(eda_vis_path + 'member5_pca_scatterplot.png')
plt.show()
```

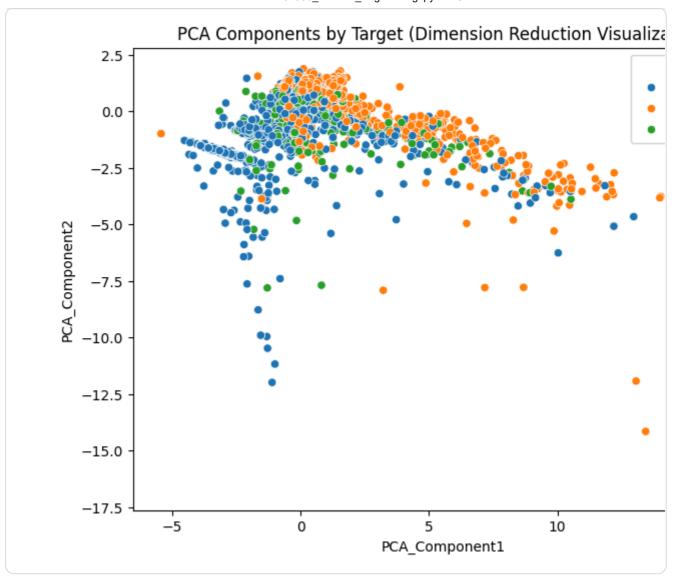
-0.986890

1.224100

0.884045

-1.621948

print(f"Processed features saved to: {processed path}")



Interpretation

This PCA plot shows that while graduates and dropouts have some separation, their points still overlap a lot, and enrolled students are mostly scattered among them, meaning the groups are not clearly distinct.