implementation_unsupervised

November 30, 2025

1 Unsupervised Learning: Implementation Notebook

This notebook explores the dataset without a target label, then applies K-Means to find groups. I kept the steps simple and clearly commented:

- Load features
- Quick EDA
- Scale numeric columns
- PCA for a 2D view
- K-Means clustering
- Silhouette score and a scatter plot

At the end, cluster labels and metrics are saved in `data/processed/`.

[22]:
```python
# Clean imports for unsupervised workflow
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

from src.data_io import load_unsupervised_features

unsup_df = load_unsupervised_features()
print("Shape:", unsup_df.shape)
unsup_df.head()
```

```
Shape: (2000, 18)
```

[22]:
```
   age  gender  daily_screen_time_hours  phone_usage_hours  \
0   51       0                      4.8                3.4
1   64       1                      3.9                3.5
2   41       2                     10.5                2.1
3   27       2                      8.8                0.0
4   55       1                      5.9                1.7
```

```
   laptop_usage_hours  tablet_usage_hours  tv_usage_hours  social_media_hours  \
0                 1.3                 1.6             1.6                 4.1
1                 1.8                 0.9             2.0                 2.7
2                 2.6                 0.7             2.2                 3.0
3                 0.0                 0.7             2.5                 3.3
4                 1.1                 1.5             1.6                 1.1

   work_related_hours  entertainment_hours  gaming_hours  \
0                 2.0                  1.0           1.7
1                 3.1                  1.0           1.5
2                 2.8                  4.1           1.7
3                 1.6                  1.3           0.4
4                 3.6                  0.8           0.8

   sleep_duration_hours  mood_rating  physical_activity_hours_per_week  \
0                   6.6            6                               0.7
1                   4.5            5                               4.3
2                   7.1            5                               3.1
3                   5.1           10                               0.0
4                   7.4            8                               3.0

   uses_wellness_apps  eats_healthy  caffeine_intake_mg_per_day  \
0                   1             1                       125.2
1                   0             1                       150.4
2                   0             0                       187.9
3                   0             1                        73.6
4                   1             1                       217.5

   mindfulness_minutes_per_day
0                          4.0
1                          6.5
2                          6.9
3                          4.8
4                          0.0
```

[23]:
```python
# Load configuration
from pathlib import Path
import yaml
config_path = Path('config.yaml')
config = {}
if config_path.exists():
    with open(config_path, 'r', encoding='utf-8') as f:
        config = yaml.safe_load(f) or {}
config
```

[23]:
```
{'paths': {'supervised': 'data/raw/clean_supervised.csv',
  'unsupervised': 'data/raw/unsupervised_no_target.csv'},
```

```
 'supervised': {'target': 'mental_health_score',
  'test_size': 0.2,
  'random_state': 42},
 'unsupervised': {'use_numeric_only': True, 'random_state': 42, 'k': 3}}
```

1.1 Exploratory Data Analysis

[24]:
```
# Quick EDA
unsup_df.info()
display(unsup_df.describe(include='all'))
if unsup_df.select_dtypes(include=np.number).shape[1] > 1:
    plt.figure(figsize=(8,6)); sns.heatmap(unsup_df.select_dtypes(include=np.
 ↪number).corr(), cmap='coolwarm'); plt.title('Numeric Correlations'); plt.
 ↪show()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 18 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   age                             2000 non-null   int64
 1   gender                          2000 non-null   int64
 2   daily_screen_time_hours         2000 non-null   float64
 3   phone_usage_hours               2000 non-null   float64
 4   laptop_usage_hours              2000 non-null   float64
 5   tablet_usage_hours              2000 non-null   float64
 6   tv_usage_hours                  2000 non-null   float64
 7   social_media_hours              2000 non-null   float64
 8   work_related_hours              2000 non-null   float64
 9   entertainment_hours             2000 non-null   float64
 10  gaming_hours                    2000 non-null   float64
 11  sleep_duration_hours            2000 non-null   float64
 12  mood_rating                     2000 non-null   int64
 13  physical_activity_hours_per_week  2000 non-null   float64
 14  uses_wellness_apps              2000 non-null   int64
 15  eats_healthy                    2000 non-null   int64
 16  caffeine_intake_mg_per_day      2000 non-null   float64
 17  mindfulness_minutes_per_day     2000 non-null   float64
dtypes: float64(13), int64(5)
memory usage: 281.4 KB
```

```
               age     gender  daily_screen_time_hours  phone_usage_hours  \
count  2000.000000  2000.0000              2000.000000        2000.000000
mean     38.805500     0.6240                 6.025600           3.023700
std      14.929203     0.6464                 1.974123           1.449399
min      13.000000     0.0000                 0.000000           0.000000
25%      26.000000     0.0000                 4.700000           2.000000
50%      39.000000     1.0000                 6.000000           3.000000
```

75%	51.000000	1.0000	7.325000	4.000000
max	64.000000	2.0000	13.300000	8.400000

	laptop_usage_hours	tablet_usage_hours	tv_usage_hours \
count	2000.000000	2000.000000	2000.000000
mean	1.999950	0.995650	1.503700
std	0.997949	0.492714	0.959003
min	0.000000	0.000000	0.000000
25%	1.300000	0.600000	0.800000
50%	2.000000	1.000000	1.500000
75%	2.700000	1.300000	2.200000
max	5.600000	2.500000	4.700000

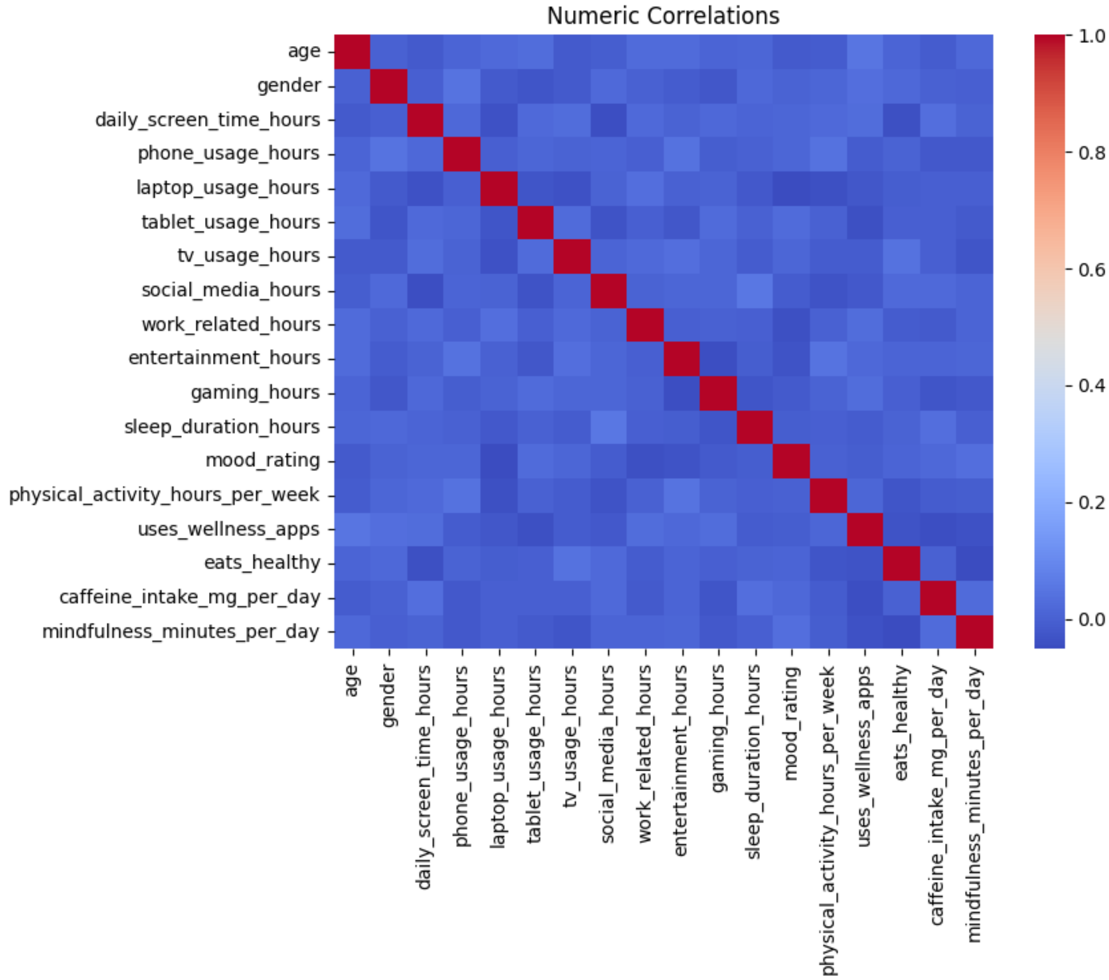
	social_media_hours	work_related_hours	entertainment_hours \
count	2000.000000	2000.000000	2000.00000
mean	2.039200	2.010250	2.46735
std	1.133435	1.116111	1.23686
min	0.000000	0.000000	0.00000
25%	1.200000	1.200000	1.60000
50%	2.000000	2.000000	2.40000
75%	2.800000	2.800000	3.30000
max	5.800000	5.900000	6.80000

	gaming_hours	sleep_duration_hours	mood_rating \
count	2000.0000	2000.000000	2000.000000
mean	1.2795	6.537550	5.591000
std	0.8945	1.203856	2.899814
min	0.0000	3.000000	1.000000
25%	0.6000	5.700000	3.000000
50%	1.2000	6.600000	6.000000
75%	1.9000	7.400000	8.000000
max	4.0000	10.000000	10.000000

	physical_activity_hours_per_week	uses_wellness_apps	eats_healthy \
count	2000.000000	2000.000000	2000.000000
mean	3.087150	0.387500	0.507500
std	1.885258	0.487301	0.500069
min	0.000000	0.000000	0.000000
25%	1.600000	0.000000	0.000000
50%	3.000000	0.000000	1.000000
75%	4.400000	1.000000	1.000000
max	9.700000	1.000000	1.000000

	caffeine_intake_mg_per_day	mindfulness_minutes_per_day
count	2000.00000	2000.000000
mean	148.07970	10.753750
std	48.86066	7.340269
min	0.80000	0.000000

```
25%              113.90000          4.900000
50%              147.45000         10.400000
75%              180.70000         15.800000
max              364.90000         36.400000
```

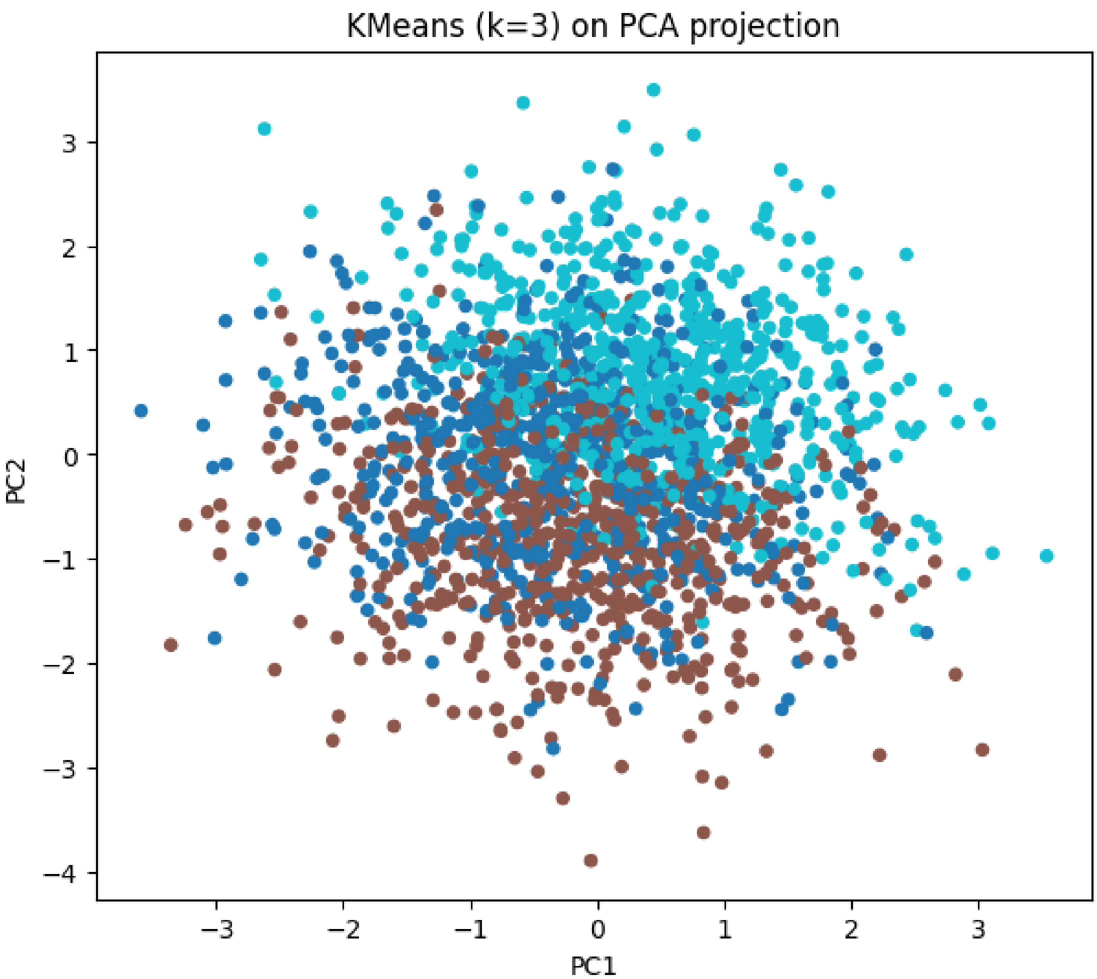


1.2 Scaling, PCA, and Clustering

[25]:
```python
# Select numeric features (drop non-numeric)
num_df = unsup_df.select_dtypes(include=np.number).copy()
scaler = StandardScaler()
X_scaled = scaler.fit_transform(num_df)

# PCA to 2 components for visualization
pca = PCA(n_components=2, random_state=42)
X_pca = pca.fit_transform(X_scaled)
print('Explained variance:', pca.explained_variance_ratio_)
```

```
# KMeans clustering (k from config or 3)
k = int(config.get('unsupervised', {}).get('k', 3))
km = KMeans(n_clusters=k, n_init='auto', random_state=42)
labels = km.fit_predict(X_scaled)

sil = silhouette_score(X_scaled, labels)
print('Silhouette score:', sil)

# Plot clusters in PCA space
plt.figure(figsize=(7,6))
plt.scatter(X_pca[:,0], X_pca[:,1], c=labels, cmap='tab10', s=20)
plt.title(f'KMeans (k={k}) on PCA projection')
plt.xlabel('PC1'); plt.ylabel('PC2'); plt.show()
```

```
Explained variance: [0.06426934 0.06384612]
Silhouette score: 0.03798480284443637
```



"The silhouette score is very low (~0.038), indicating weak or overlapping cluster structure. This means lifestyle behaviours in this dataset do not naturally separate into clear groups."

1.3 Save Artifacts

[26]:
```
# Save labels and metrics
from pathlib import Path
import json
processed_dir = Path(config.get('paths', {}).get('processed', 'data/processed'))
processed_dir.mkdir(parents=True, exist_ok=True)
labels_path = processed_dir / 'unsupervised_kmeans_labels.csv'
metrics_path = processed_dir / 'unsupervised_metrics.json'

out = pd.DataFrame({'cluster': labels})
out.to_csv(labels_path, index=False)
with open(metrics_path, 'w', encoding='utf-8') as f:
    json.dump({'k': int(config.get('unsupervised', {}).get('k', 3)),␣
 ↪'silhouette': float(sil)}, f, indent=2)
labels_path, metrics_path
```

[26]:
```
(WindowsPath('data/processed/unsupervised_kmeans_labels.csv'),
 WindowsPath('data/processed/unsupervised_metrics.json'))
```

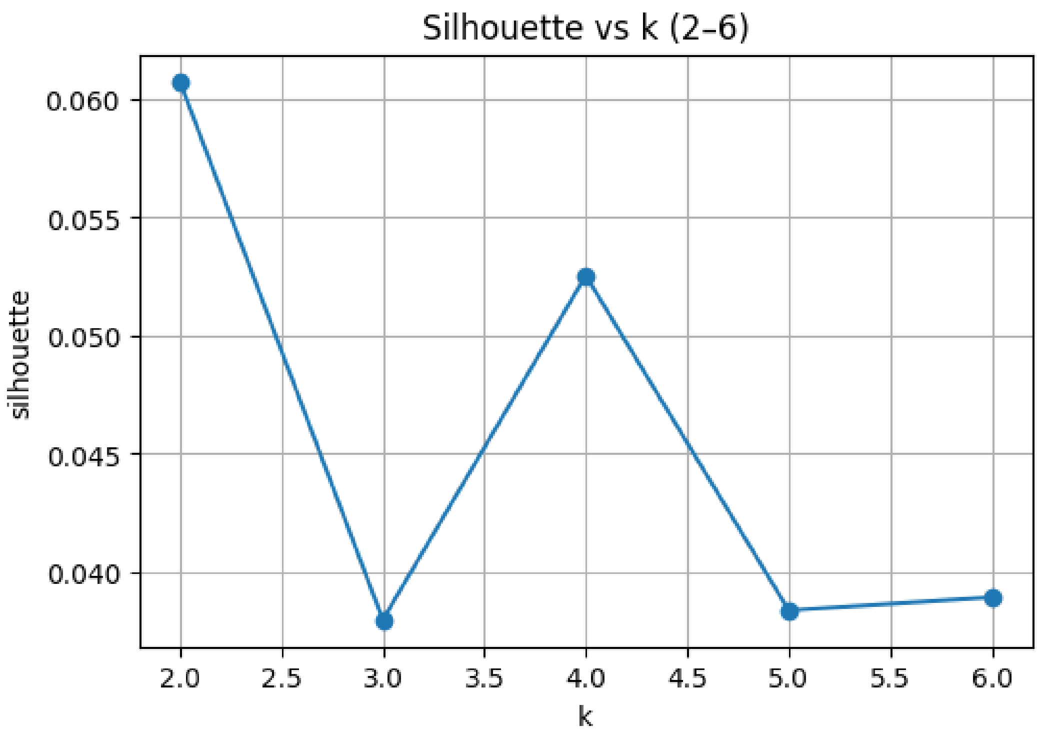
1.3.1 K selection via silhouette (2–6)

We test a few k values and report silhouette scores. A low score means clusters overlap and the separation is weak.

[27]:
```
# Silhouette sweep for k=2..6
import pandas as pd
from sklearn.metrics import silhouette_score
scores = []
for k_try in range(2, 7):
    km_try = KMeans(n_clusters=k_try, n_init='auto', random_state=42)
    lbl = km_try.fit_predict(X_scaled)
    s = silhouette_score(X_scaled, lbl)
    scores.append({'k': k_try, 'silhouette': float(s)})
sil_df = pd.DataFrame(scores)
display(sil_df)

plt.figure(figsize=(6,4))
plt.plot(sil_df['k'], sil_df['silhouette'], marker='o')
plt.title('Silhouette vs k (2-6)')
plt.xlabel('k')
plt.ylabel('silhouette')
plt.grid(True)
```

```
plt.show()
```

```
   k  silhouette
0  2    0.060755
1  3    0.037985
2  4    0.052541
3  5    0.038384
4  6    0.038933
```



1.3.2 Cluster interpretation

We join cluster labels back to the original data and compute simple per-cluster means. If the example columns are present, we show those; otherwise we fall back to a few numeric columns.

[28]:
```
# Join labels, compute per-cluster means, and print a readable summary
unsup_df_with_cluster = unsup_df.copy()
unsup_df_with_cluster['cluster'] = labels

# Prefer these columns if present; else fallback to top 3 numeric columns
preferred = ['daily_screen_time_hours', 'sleep_duration_hours', 'mood_rating']
available = [c for c in preferred if c in unsup_df_with_cluster.columns]
if not available:
    num_cols = unsup_df_with_cluster.select_dtypes(include=np.number).columns.
 ↪tolist()
```

```python
    available = [c for c in num_cols if c != 'cluster'][:3]

print('Columns used for interpretation:', available)
cluster_means = unsup_df_with_cluster.groupby('cluster')[available].mean().
 ↪round(2)
display(cluster_means)

# Simple textual summary vs overall mean
overall = unsup_df_with_cluster[available].mean()
print('\nQuick interpretation (relative to overall mean):')
for cl in sorted(unsup_df_with_cluster['cluster'].unique()):
    deltas = (cluster_means.loc[cl] - overall)
    deltas_sorted = deltas.sort_values()
    low = deltas_sorted.index[:1].tolist()
    high = deltas_sorted.index[-1:].tolist()
    print(f"- Cluster {cl}: higher {high}; lower {low}")
```

```
Columns used for interpretation: ['daily_screen_time_hours',
'sleep_duration_hours', 'mood_rating']
```

cluster	daily_screen_time_hours	sleep_duration_hours	mood_rating
0	6.32	6.65	5.86
1	5.71	6.16	3.73
2	6.05	6.79	7.15

```
Quick interpretation (relative to overall mean):
- Cluster 0: higher ['daily_screen_time_hours']; lower ['sleep_duration_hours']
- Cluster 1: higher ['daily_screen_time_hours']; lower ['mood_rating']
- Cluster 2: higher ['mood_rating']; lower ['daily_screen_time_hours']
```