NIJs Recidivism

In this project, KMeans clustering was applied as an unsupervised learning approach to group individuals in the NIJ Recidivism dataset based on demographic, employment, and criminal history features. The goal of clustering was to identify latent patterns among individuals without using recidivism outcomes as labels, allowing the data itself to reveal groups with similar characteristics. This unsupervised approach is appropriate because it does not rely on pre-defined outcomes, and it can uncover meaningful profiles that might inform targeted interventions or rehabilitation strategies.

Citation

National Institute of Justice. (2021). NIJ's Recidivism Challenge Full Dataset [Dataset]. Office of Justice Programs, U.S. Department of Justice. Retrieved from https://catalog.data.gov/dataset/nijs-recidivism-challenge-full-dataset

Set-Up

In [1]:
```
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

sns.set(style="whitegrid")
```

EDA

Initial data exploration revealed a mix of numeric and categorical features with varying levels of missing data. Numeric variables such as Percent_Days_Employed, Jobs_Per_Year, and Age_at_Release were cleaned by converting text ranges and categories into numeric representations and filling missing values with the median. Categorical features, including Gender and Race, were one-hot encoded. Distributional analysis showed that most individuals were male, aged between 30 and 35 at release, and racially diverse. Employment levels varied widely, from near-zero employment to full employment, while supervision risk scores were generally moderate to high. Correlation analysis indicated that employment metrics were negatively correlated with recidivism, while risk scores were slightly positively correlated. Standard scaling was applied to numeric features in preparation for PCA and clustering.

In [2]:
```
df = pd.read_csv('NIJ_s_Recidivism_Challenge_Full_Dataset.csv')

df.head()
```

Out[2]:

	ID	Gender	Race	Age_at_Release	Residence_PUMA	Gang_Affiliated	Supervision_Risk_
0	1	M	BLACK	43-47	16	False	
1	2	M	BLACK	33-37	16	False	
2	3	M	BLACK	48 or older	24	False	
3	4	M	WHITE	38-42	16	False	
4	5	M	WHITE	33-37	16	False	

5 rows × 54 columns

In [3]:
```
df.info()

df.describe()

df.isnull().sum()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25835 entries, 0 to 25834
Data columns (total 54 columns):
 #   Column                                             Non-Null Count  Dtype  
---  ------                                             --------------  -----  
 0   ID                                                 25835 non-null  int64  
 1   Gender                                             25835 non-null  object 
 2   Race                                               25835 non-null  object 
 3   Age_at_Release                                     25835 non-null  object 
 4   Residence_PUMA                                     25835 non-null  int64  
 5   Gang_Affiliated                                    22668 non-null  object 
 6   Supervision_Risk_Score_First                       25360 non-null  float64
 7   Supervision_Level_First                            24115 non-null  object 
 8   Education_Level                                    25835 non-null  object 
 9   Dependents                                         25835 non-null  object 
 10  Prison_Offense                                     22558 non-null  object 
 11  Prison_Years                                       25835 non-null  object 
 12  Prior_Arrest_Episodes_Felony                       25835 non-null  object 
 13  Prior_Arrest_Episodes_Misd                         25835 non-null  object 
 14  Prior_Arrest_Episodes_Violent                      25835 non-null  object 
 15  Prior_Arrest_Episodes_Property                     25835 non-null  object 
 16  Prior_Arrest_Episodes_Drug                         25835 non-null  object 
 17  Prior_Arrest_Episodes_PPViolationCharges           25835 non-null  object 
 18  Prior_Arrest_Episodes_DVCharges                    25835 non-null  bool   
 19  Prior_Arrest_Episodes_GunCharges                   25835 non-null  bool   
 20  Prior_Conviction_Episodes_Felony                   25835 non-null  object 
 21  Prior_Conviction_Episodes_Misd                     25835 non-null  object 
 22  Prior_Conviction_Episodes_Viol                     25835 non-null  bool   
 23  Prior_Conviction_Episodes_Prop                     25835 non-null  object 
 24  Prior_Conviction_Episodes_Drug                     25835 non-null  object 
 25  Prior_Conviction_Episodes_PPViolationCharges       25835 non-null  bool   
 26  Prior_Conviction_Episodes_DomesticViolenceCharges  25835 non-null  bool   
 27  Prior_Conviction_Episodes_GunCharges               25835 non-null  bool   
 28  Prior_Revocations_Parole                           25835 non-null  bool   
 29  Prior_Revocations_Probation                        25835 non-null  bool   
 30  Condition_MH_SA                                    25835 non-null  bool   
 31  Condition_Cog_Ed                                   25835 non-null  bool   
 32  Condition_Other                                    25835 non-null  bool   
 33  Violations_ElectronicMonitoring                    25835 non-null  bool   
 34  Violations_Instruction                             25835 non-null  bool   
 35  Violations_FailToReport                            25835 non-null  bool   
 36  Violations_MoveWithoutPermission                   25835 non-null  bool   
 37  Delinquency_Reports                                25835 non-null  object 
 38  Program_Attendances                                25835 non-null  object 
 39  Program_UnexcusedAbsences                          25835 non-null  object 
 40  Residence_Changes                                  25835 non-null  object 
 41  Avg_Days_per_DrugTest                              19732 non-null  float64
 42  DrugTests_THC_Positive                             20663 non-null  float64
 43  DrugTests_Cocaine_Positive                         20663 non-null  float64
 44  DrugTests_Meth_Positive                            20663 non-null  float64
 45  DrugTests_Other_Positive                           20663 non-null  float64
 46  Percent_Days_Employed                              25373 non-null  float64
 47  Jobs_Per_Year                                      25027 non-null  float64
 48  Employment_Exempt                                  25835 non-null  bool   
 49  Recidivism_Within_3years                           25835 non-null  bool   
 50  Recidivism_Arrest_Year1                            25835 non-null  bool   
```

```
 51  Recidivism_Arrest_Year2                            25835 non-null  bool
 52  Recidivism_Arrest_Year3                            25835 non-null  bool
 53  Training_Sample                                    25835 non-null  int64
dtypes: bool(20), float64(8), int64(3), object(23)
memory usage: 7.2+ MB
```

Out[3]:
```
ID                                                   0
Gender                                               0
Race                                                 0
Age_at_Release                                       0
Residence_PUMA                                       0
Gang_Affiliated                                   3167
Supervision_Risk_Score_First                       475
Supervision_Level_First                           1720
Education_Level                                      0
Dependents                                           0
Prison_Offense                                    3277
Prison_Years                                         0
Prior_Arrest_Episodes_Felony                         0
Prior_Arrest_Episodes_Misd                           0
Prior_Arrest_Episodes_Violent                        0
Prior_Arrest_Episodes_Property                       0
Prior_Arrest_Episodes_Drug                           0
Prior_Arrest_Episodes_PPViolationCharges             0
Prior_Arrest_Episodes_DVCharges                      0
Prior_Arrest_Episodes_GunCharges                     0
Prior_Conviction_Episodes_Felony                     0
Prior_Conviction_Episodes_Misd                       0
Prior_Conviction_Episodes_Viol                       0
Prior_Conviction_Episodes_Prop                       0
Prior_Conviction_Episodes_Drug                       0
Prior_Conviction_Episodes_PPViolationCharges         0
Prior_Conviction_Episodes_DomesticViolenceCharges    0
Prior_Conviction_Episodes_GunCharges                 0
Prior_Revocations_Parole                             0
Prior_Revocations_Probation                          0
Condition_MH_SA                                      0
Condition_Cog_Ed                                     0
Condition_Other                                      0
Violations_ElectronicMonitoring                      0
Violations_Instruction                               0
Violations_FailToReport                              0
Violations_MoveWithoutPermission                     0
Delinquency_Reports                                  0
Program_Attendances                                  0
Program_UnexcusedAbsences                            0
Residence_Changes                                    0
Avg_Days_per_DrugTest                             6103
DrugTests_THC_Positive                            5172
DrugTests_Cocaine_Positive                        5172
DrugTests_Meth_Positive                           5172
DrugTests_Other_Positive                          5172
Percent_Days_Employed                              462
Jobs_Per_Year                                      808
Employment_Exempt                                    0
Recidivism_Within_3years                             0
Recidivism_Arrest_Year1                              0
Recidivism_Arrest_Year2                              0
Recidivism_Arrest_Year3                              0
Training_Sample                                      0
dtype: int64
```

In [4]:
```
# unique values in these columns
for col in ['Dependents', 'Jobs_Per_Year']:
    print(col, df[col].unique())
def convert_to_numeric(x):
    if pd.isnull(x):
        return np.nan
    elif isinstance(x, str) and 'or more' in x:
        return float(x.split()[0])  # take the first number
    else:
        return float(x)

df['Dependents_numeric'] = df['Dependents'].apply(convert_to_numeric)
df['Jobs_Per_Year_numeric'] = df['Jobs_Per_Year'].apply(convert_to_numeric)
```

```
Dependents ['3 or more' '1' '0' '2']
Jobs_Per_Year [0.44761029 2.         0.         ... 0.2818287  1.37484316 1.3346528
6]
```

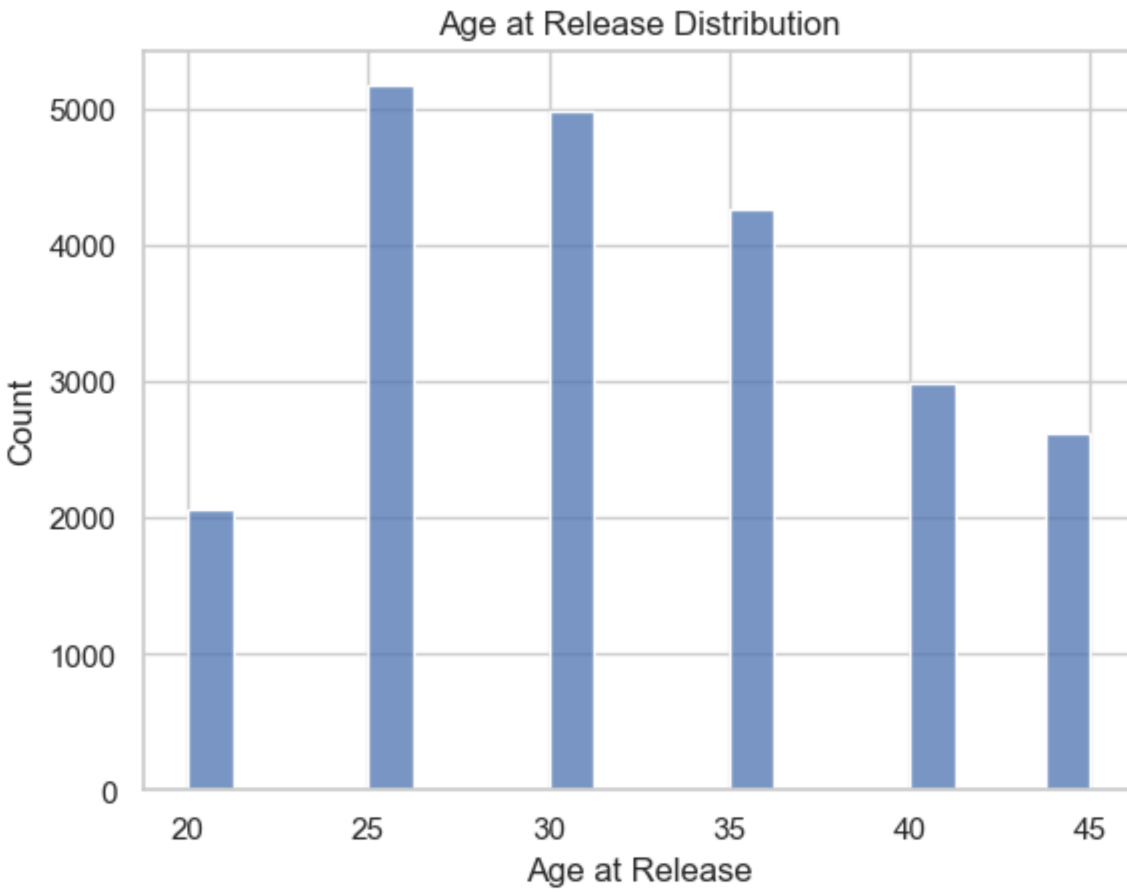
In [5]:
```
# convert ranges to midpoint
def range_to_midpoint(x):
    if isinstance(x, str) and '-' in x:
        start, end = x.split('-')
        return (float(start) + float(end)) / 2
    else:
        return np.nan

df['Age_at_Release_numeric'] = df['Age_at_Release'].apply(range_to_midpoint)
```

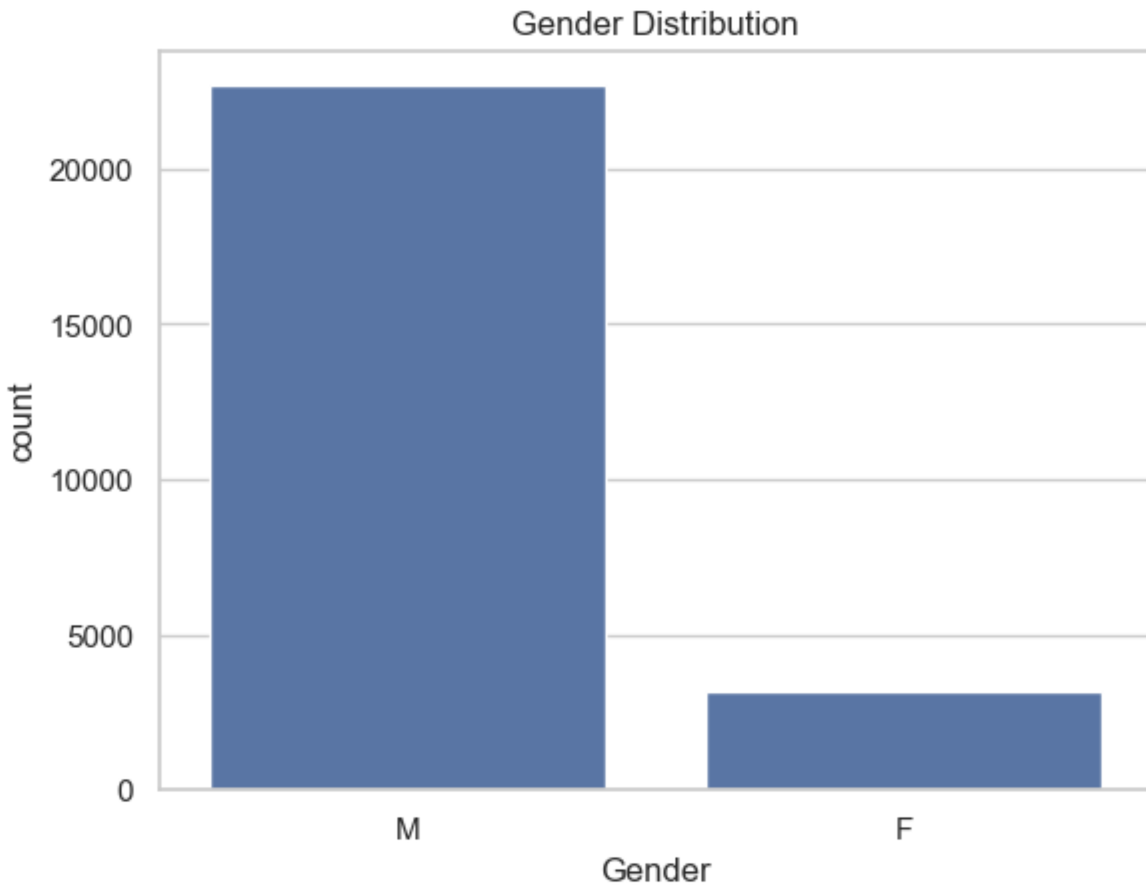
Visualize

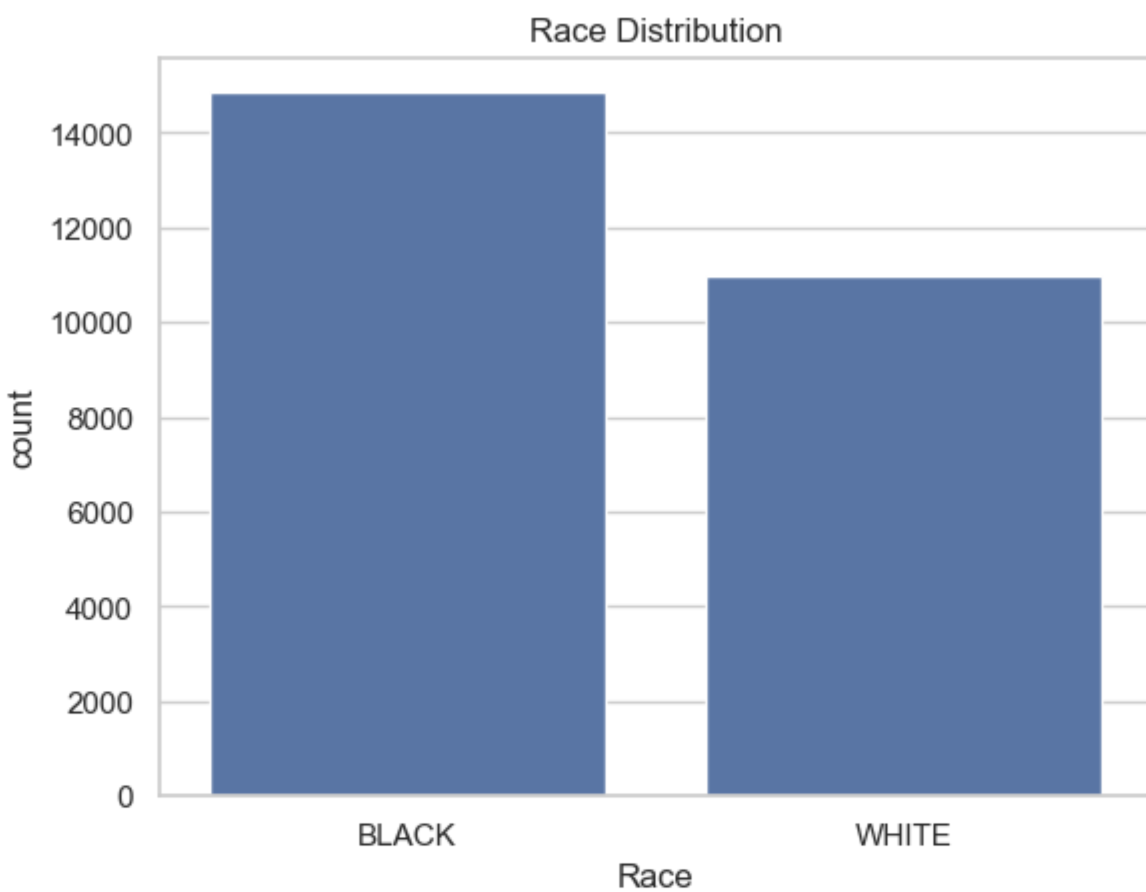
Exploratory visualization confirmed these patterns: Histograms of age, supervision risk scores, and employment showed diverse distributions, while countplots revealed gender and race breakdowns. A PCA projection provided a preliminary view of feature relationships in two-dimensional space, facilitating the subsequent clustering analysis.

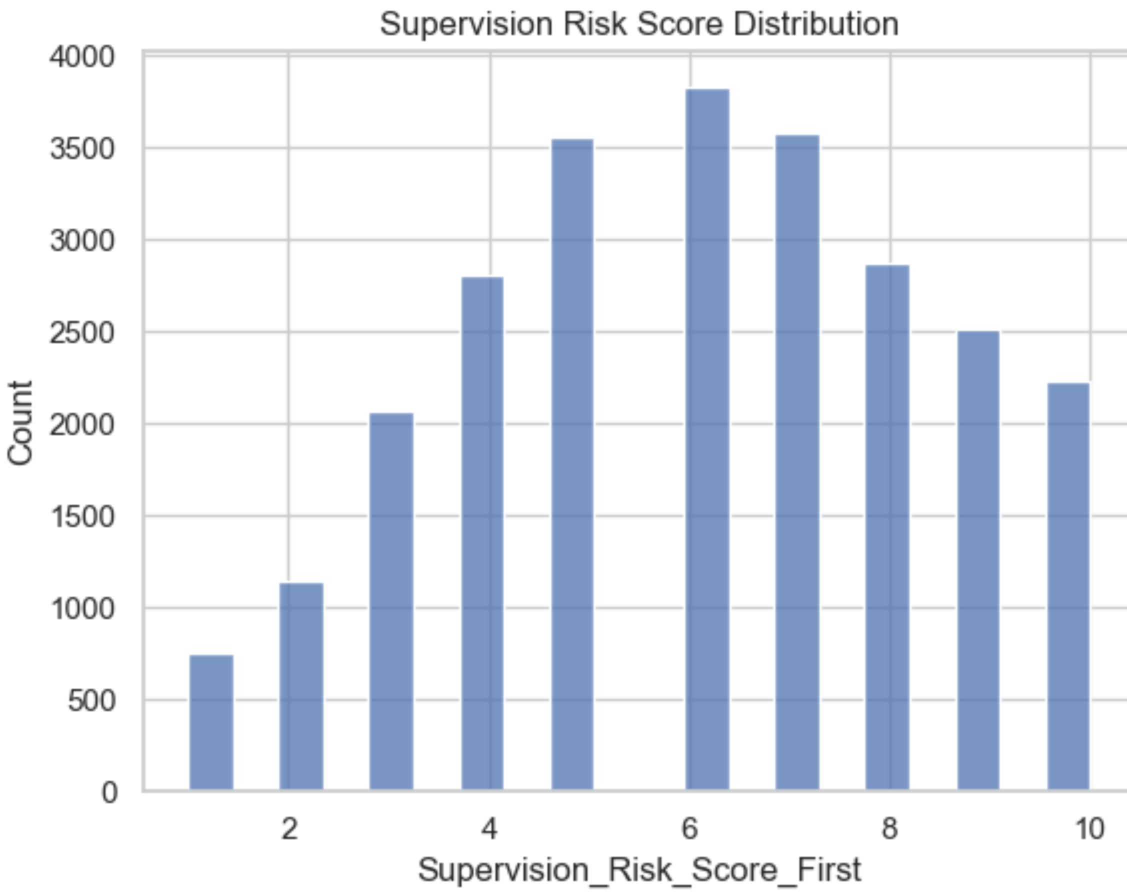
In [6]:
```
# Age distribution
sns.histplot(df['Age_at_Release_numeric'], bins=20)
plt.xlabel("Age at Release")
plt.title("Age at Release Distribution")
plt.show()


# Gender distribution
sns.countplot(x='Gender', data=df)
plt.title("Gender Distribution")
plt.show()

# Race distribution
sns.countplot(x='Race', data=df)
plt.title("Race Distribution")
plt.show()

# Supervision risk score
```

```
sns.histplot(df['Supervision_Risk_Score_First'], bins=20)
plt.title("Supervision Risk Score Distribution")
plt.show()
```



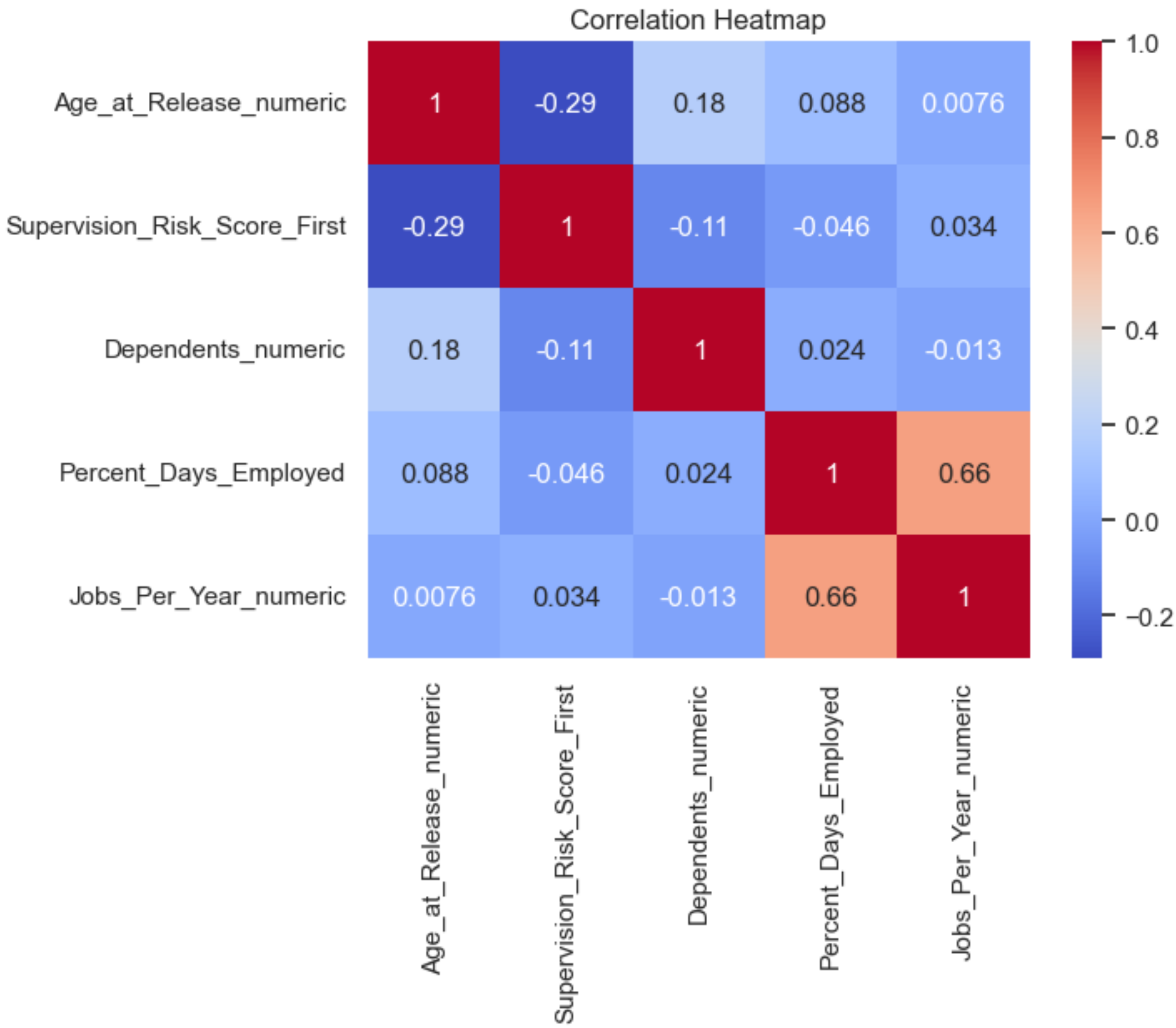

Gender Distribution
20000
15000
10000
5000
0
count
M
F
Gender


Race Distribution
14000
12000
10000
8000
6000
4000
2000
0
count
BLACK
WHITE
Race



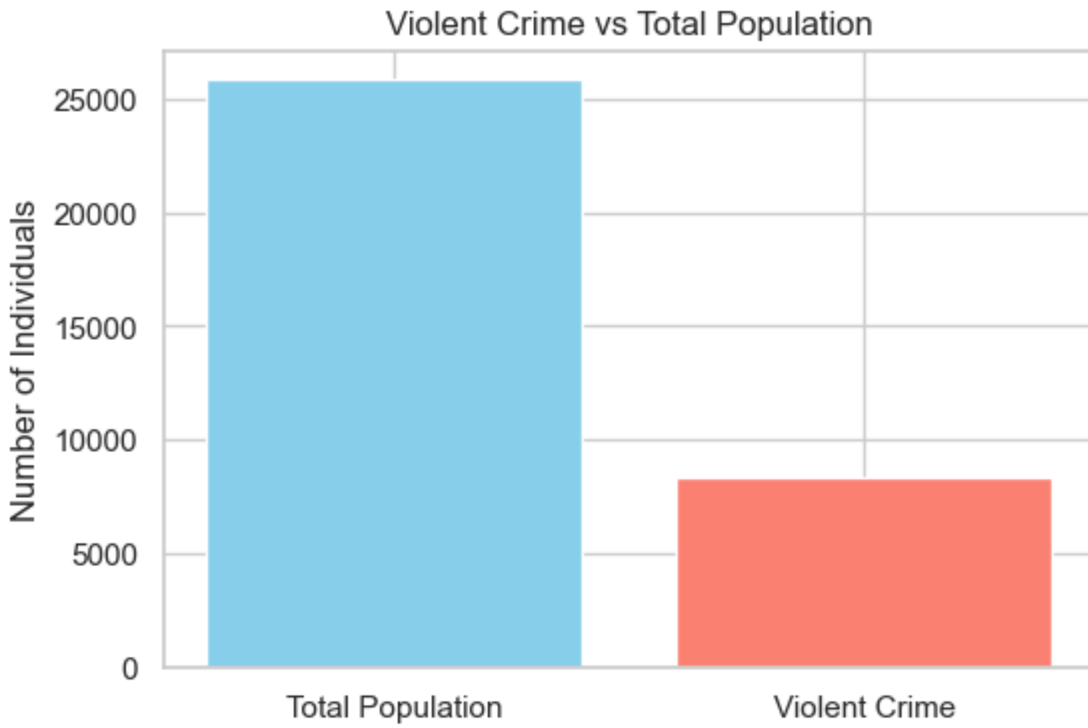
In [7]:
```
# Replace numeric_features
numeric_features = [
    'Age_at_Release_numeric',
    'Supervision_Risk_Score_First',
    'Dependents_numeric',
    'Percent_Days_Employed',
    'Jobs_Per_Year_numeric'
]

# Fill missing values
df[numeric_features] = df[numeric_features].fillna(df[numeric_features].median())
```

In [8]:
```
# Correlation heatmap
corr = df[numeric_features].corr()
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()
```



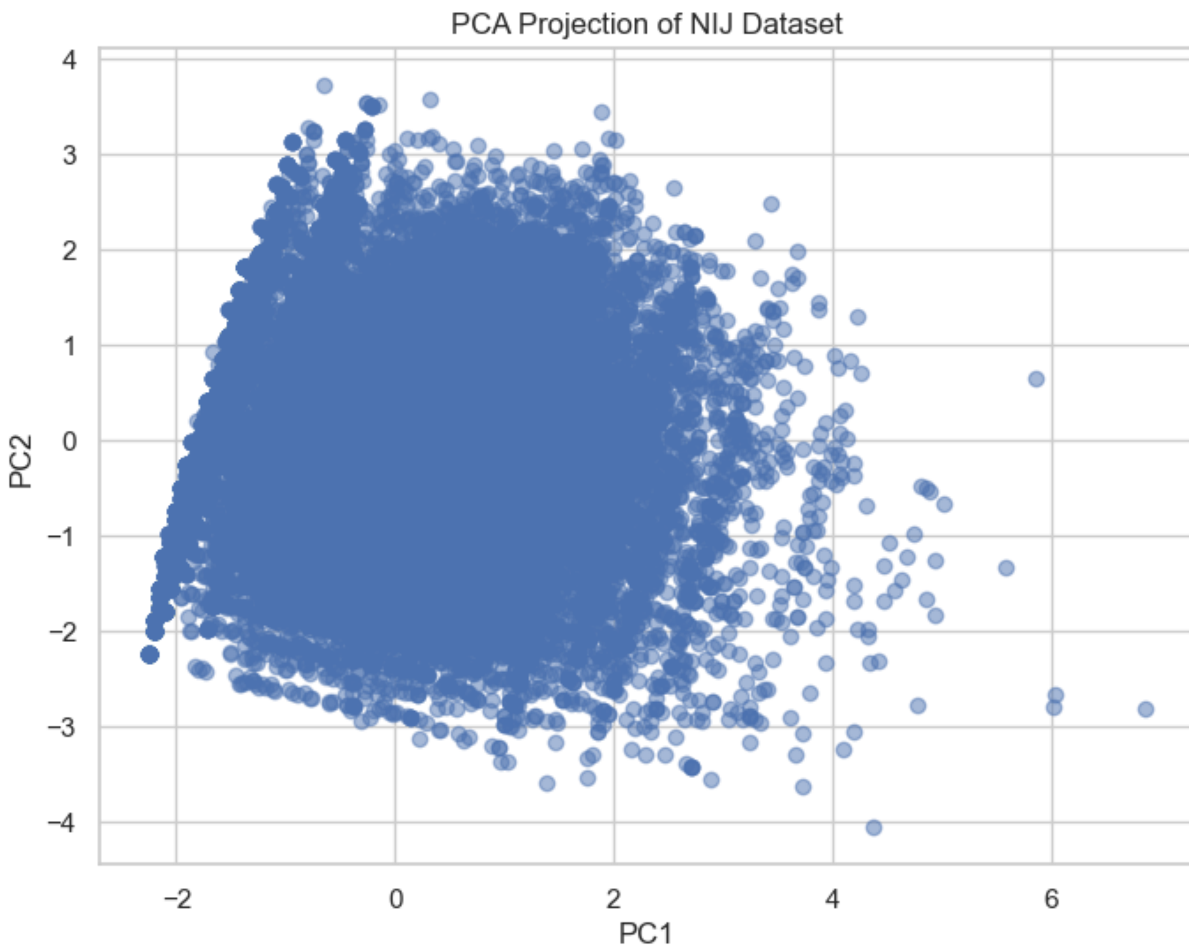
In [9]:

```
total_count = len(df)

# Count individuals with prior violent convictions
violent_count = df['Prior_Conviction_Episodes_Viol'].sum()

labels = ['Total Population', 'Violent Crime']
counts = [total_count, violent_count]

# Plot
plt.figure(figsize=(6,4))
plt.bar(labels, counts, color=['skyblue', 'salmon'])
plt.ylabel('Number of Individuals')
plt.title('Violent Crime vs Total Population')
plt.show()
```



In [10]:
```
# Fill missing numeric values with median
df[numeric_features] = df[numeric_features].fillna(df[numeric_features].median())

categorical_features = ['Race', 'Gender']
df_encoded = pd.get_dummies(df[categorical_features], drop_first=True)


# Combine numeric + encoded categorical features
X = pd.concat([df[numeric_features], df_encoded], axis=1)

# Scale data for clustering/PCA
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

In [11]:
```
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

plt.figure(figsize=(8,6))
plt.scatter(X_pca[:,0], X_pca[:,1], alpha=0.5)
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.title('PCA Projection of NIJ Dataset')
plt.show()
```



KMeans

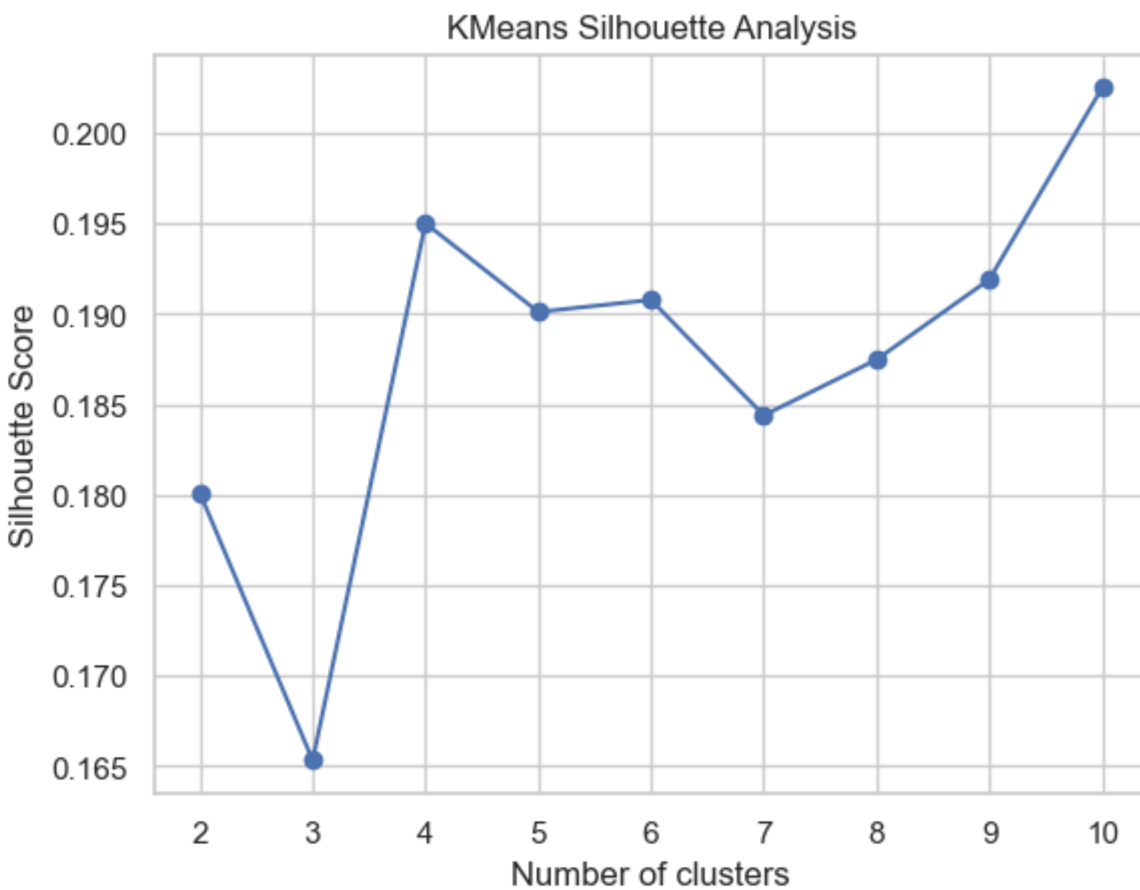
KMeans clustering was performed on scaled numeric and encoded categorical features, with the optimal number of clusters determined via silhouette analysis as four. Clusters were profiled based on age, risk score, dependents, employment, and jobs per year.

The results revealed distinct patterns: one cluster with very low employment exhibited the highest recidivism rate (71%), whereas clusters with higher employment had lower recidivism rates (45–53%). PCA visualization confirmed that the clusters were separable in two-dimensional space. Cluster labeling based on employment and risk levels provided interpretable insights, suggesting that employment is a critical protective factor against recidivism and that low-employment individuals represent a high-risk group.

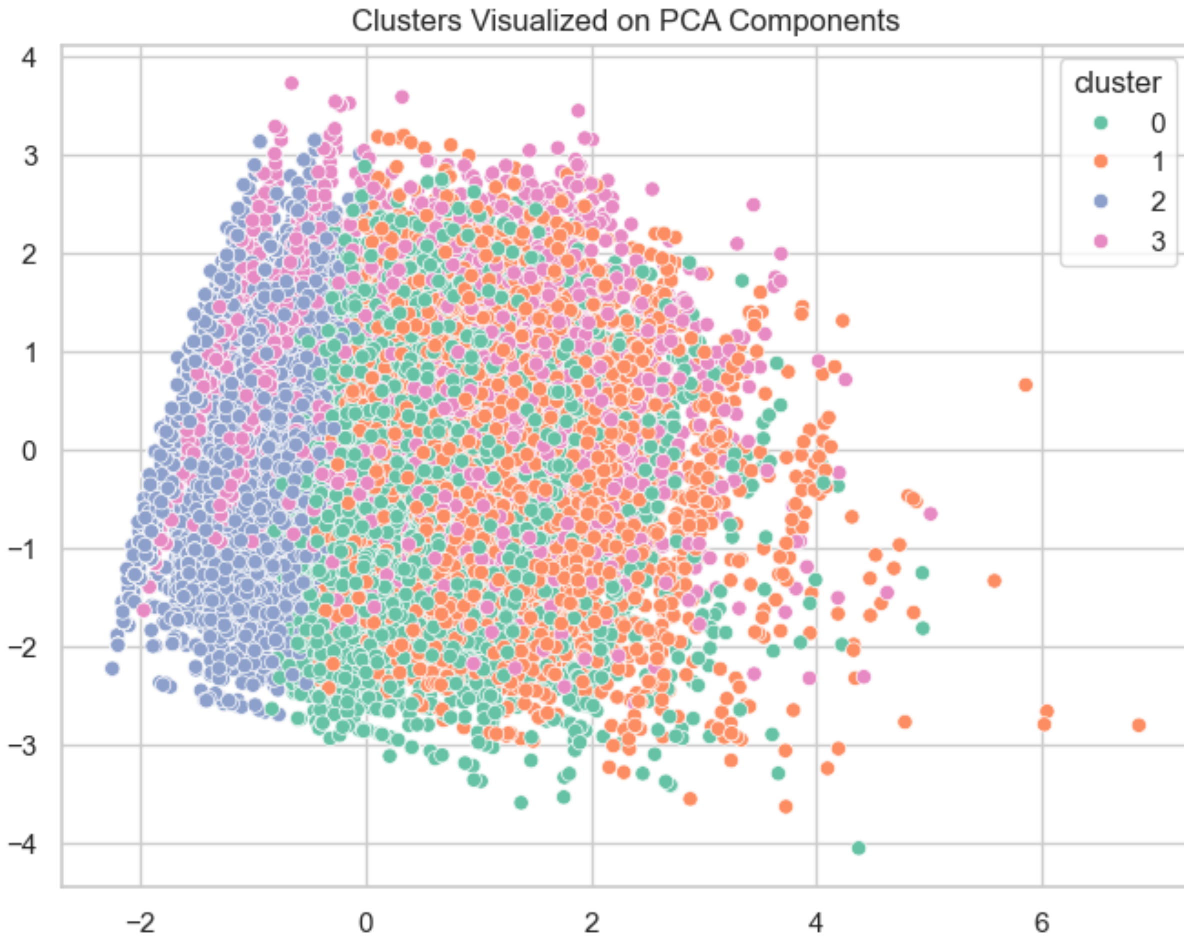
In [12]:
```
# Determine optimal number of clusters
sil_scores = []
K_range = range(2, 11)
for k in K_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    labels = kmeans.fit_predict(X_scaled)
    sil_scores.append(silhouette_score(X_scaled, labels))

# silhouette scores
```

```
plt.plot(K_range, sil_scores, marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Score')
plt.title('KMeans Silhouette Analysis')
plt.show()
```

```
C:\Users\asm3886\anaconda3\Lib\site-packages\threadpoolctl.py:1226: RuntimeWarning:
Found Intel OpenMP ('libiomp') and LLVM OpenMP ('libomp') loaded at
the same time. Both libraries are known to be incompatible and this
can cause random crashes or deadlocks on Linux when loaded in the
same Python program.
Using threadpoolctl may cause crashes or deadlocks. For more
information and possible workarounds, please see
    https://github.com/joblib/threadpoolctl/blob/master/multiple_openmp.md

  warnings.warn(msg, RuntimeWarning)
```



In [13]:
```
# Fit KMeans
kmeans = KMeans(n_clusters=4, random_state=42)
clusters = kmeans.fit_predict(X_scaled)
df['cluster'] = clusters

# Cluster in PCA space
plt.figure(figsize=(8,6))
sns.scatterplot(x=X_pca[:,0], y=X_pca[:,1], hue=df['cluster'], palette='Set2')
plt.title('Clusters Visualized on PCA Components')
plt.show()
```



In [14]:
```
# mean of numeric features
cluster_summary = df.groupby('cluster')[numeric_features].mean()

# mean recidivism rate
recidivism_rate = df.groupby('cluster')['Recidivism_Within_3years'].mean()

# Combine summaries
cluster_info = cluster_summary.copy()
cluster_info['Recidivism_Rate'] = recidivism_rate

print(cluster_info)
```

```
         Age_at_Release_numeric  Supervision_Risk_Score_First  \
cluster
0                     31.712495                      6.012110
1                     32.792531                      5.877510
2                     30.568253                      6.263661
3                     33.074250                      6.063191

         Dependents_numeric  Percent_Days_Employed  Jobs_Per_Year_numeric  \
cluster
0                  1.647386               0.807555               1.182983
1                  1.335934               0.794549               1.242640
2                  1.398816               0.045885               0.167190
3                  1.558294               0.493171               0.747794

         Recidivism_Rate
cluster
0               0.488389
1               0.527303
2               0.712445
3               0.455292
```

In [15]:

```
def name_cluster(row):
    # Risk level
    if row['Recidivism_Rate'] > 0.50:
        risk = "High-Risk"
    elif row['Recidivism_Rate'] > 0.2:
        risk = "Moderate-Risk"
    else:
        risk = "Lower-Risk"

    # Employment descriptor
    emp = row['Percent_Days_Employed']
    if emp > 0.7:
        emp_label = "High Employment"
    elif emp > 0.4:
        emp_label = "Partial Employment"
    else:
        emp_label = "Low Employment"

    return f"{risk} / {emp_label}"
```

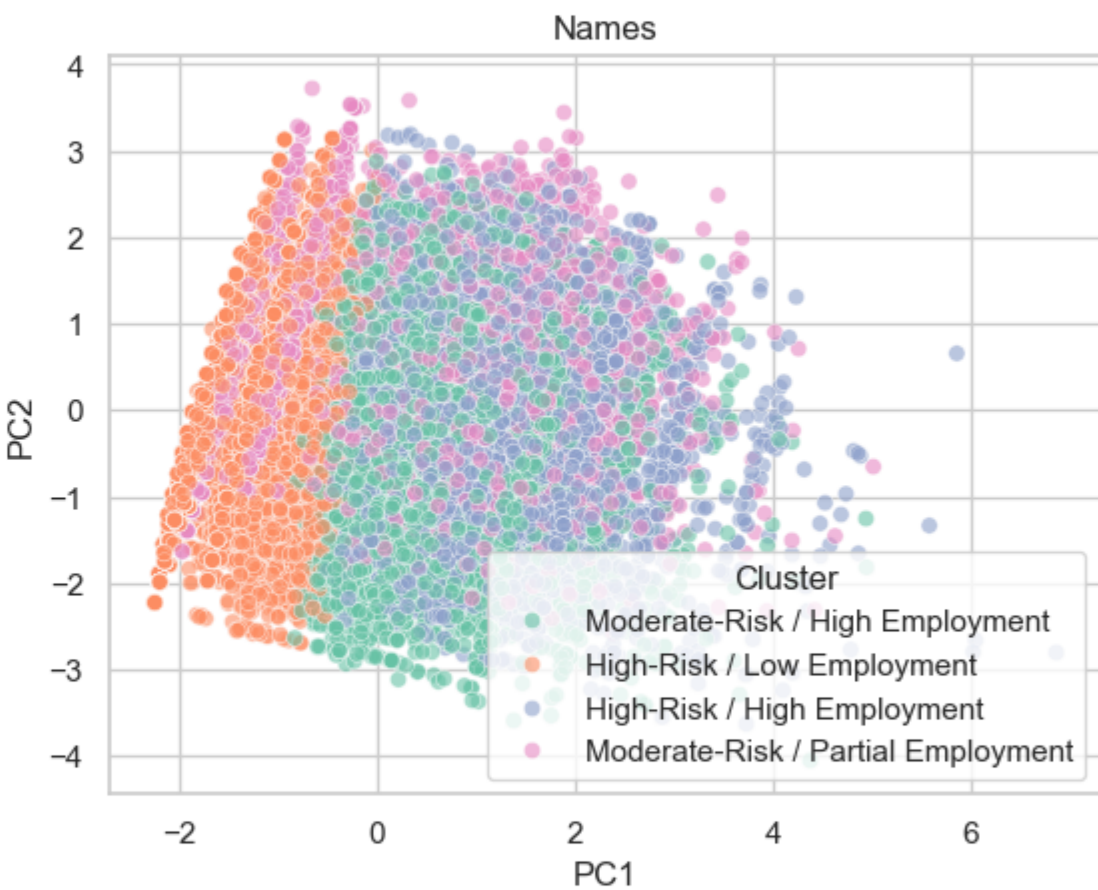
In [16]:

```
# Create a mapping from cluster number → name
cluster_names = cluster_info.apply(name_cluster, axis=1).to_dict()

# Map
df['cluster_name'] = df['cluster'].map(cluster_names)

# Preview
df[['cluster', 'cluster_name']].drop_duplicates()
```

Out[16]:

	cluster	cluster_name
0	0	Moderate-Risk / High Employment
2	2	High-Risk / Low Employment
3	1	High-Risk / High Employment
8	3	Moderate-Risk / Partial Employment

In [17]:
```
sns.scatterplot(
    x=X_pca[:,0],
    y=X_pca[:,1],
    hue=df['cluster_name'],
    palette='Set2',
    alpha=0.6
)
plt.title('Names')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.legend(title='Cluster')
plt.show()
```



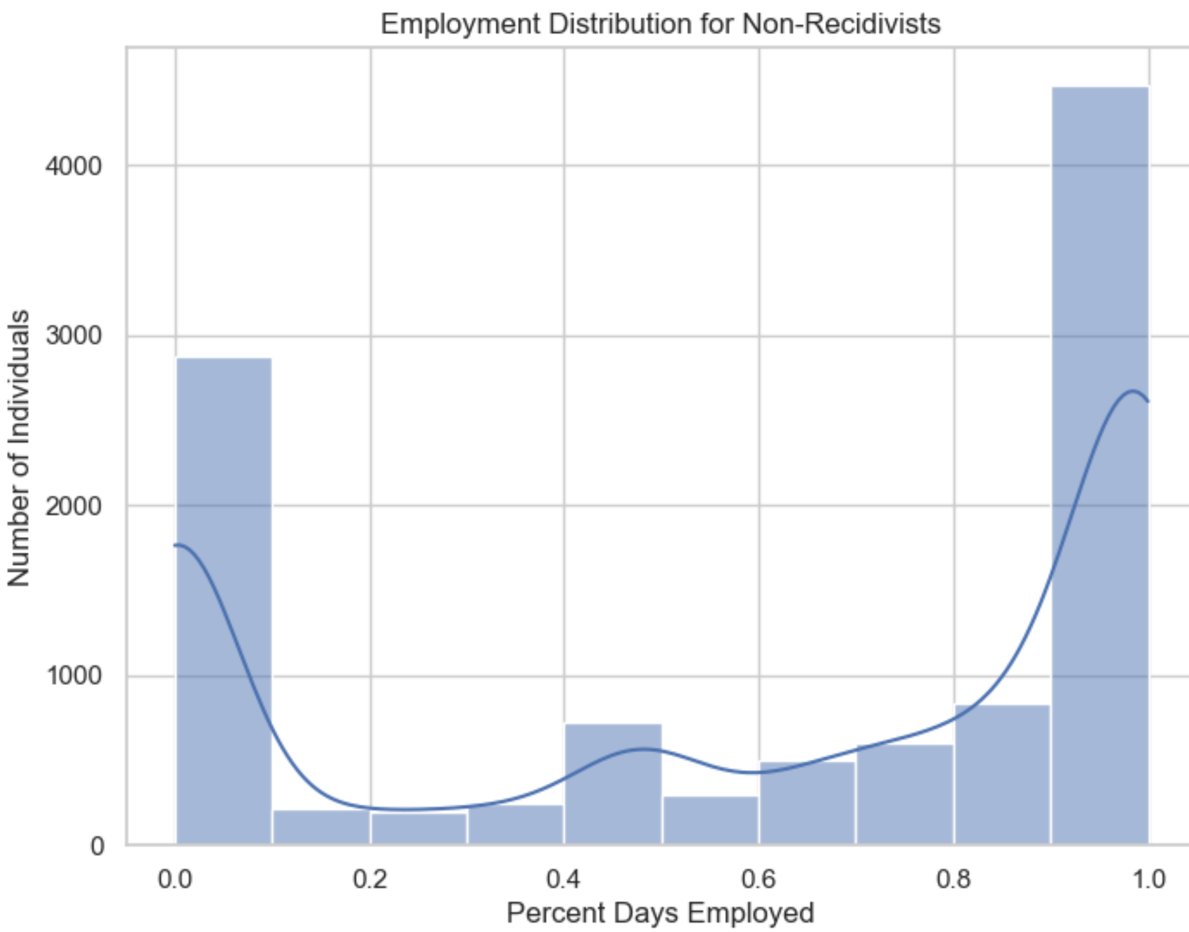
In [18]:
```
# cluster profiles
cluster_summary = df.groupby('cluster')[numeric_features].mean()
print(cluster_summary)

# Compare recidivism rates
```

```
recidivism_rate_by_cluster = df.groupby('cluster')['Recidivism_Within_3years'].mean
print(recidivism_rate_by_cluster)
```

```
         Age_at_Release_numeric  Supervision_Risk_Score_First  \
cluster
0                     31.712495                      6.012110
1                     32.792531                      5.877510
2                     30.568253                      6.263661
3                     33.074250                      6.063191

         Dependents_numeric  Percent_Days_Employed  Jobs_Per_Year_numeric
cluster
0                  1.647386               0.807555               1.182983
1                  1.335934               0.794549               1.242640
2                  1.398816               0.045885               0.167190
3                  1.558294               0.493171               0.747794
cluster
0    0.488389
1    0.527303
2    0.712445
3    0.455292
Name: Recidivism_Within_3years, dtype: float64
```

In [19]:
```
recid_cols = ['Recidivism_Arrest_Year1', 'Recidivism_Arrest_Year2', 'Recidivism_Arr

# Melt the dataframe
df_long = df.melt(
    id_vars=['ID', 'Percent_Days_Employed'],  # keep ID and employment
    value_vars=recid_cols,
    var_name='Year',
    value_name='Recidivism'
)

# 'Year' to numeric 1,2,3
df_long['Year'] = df_long['Year'].str.extract(r'(\d)').astype(int)
```

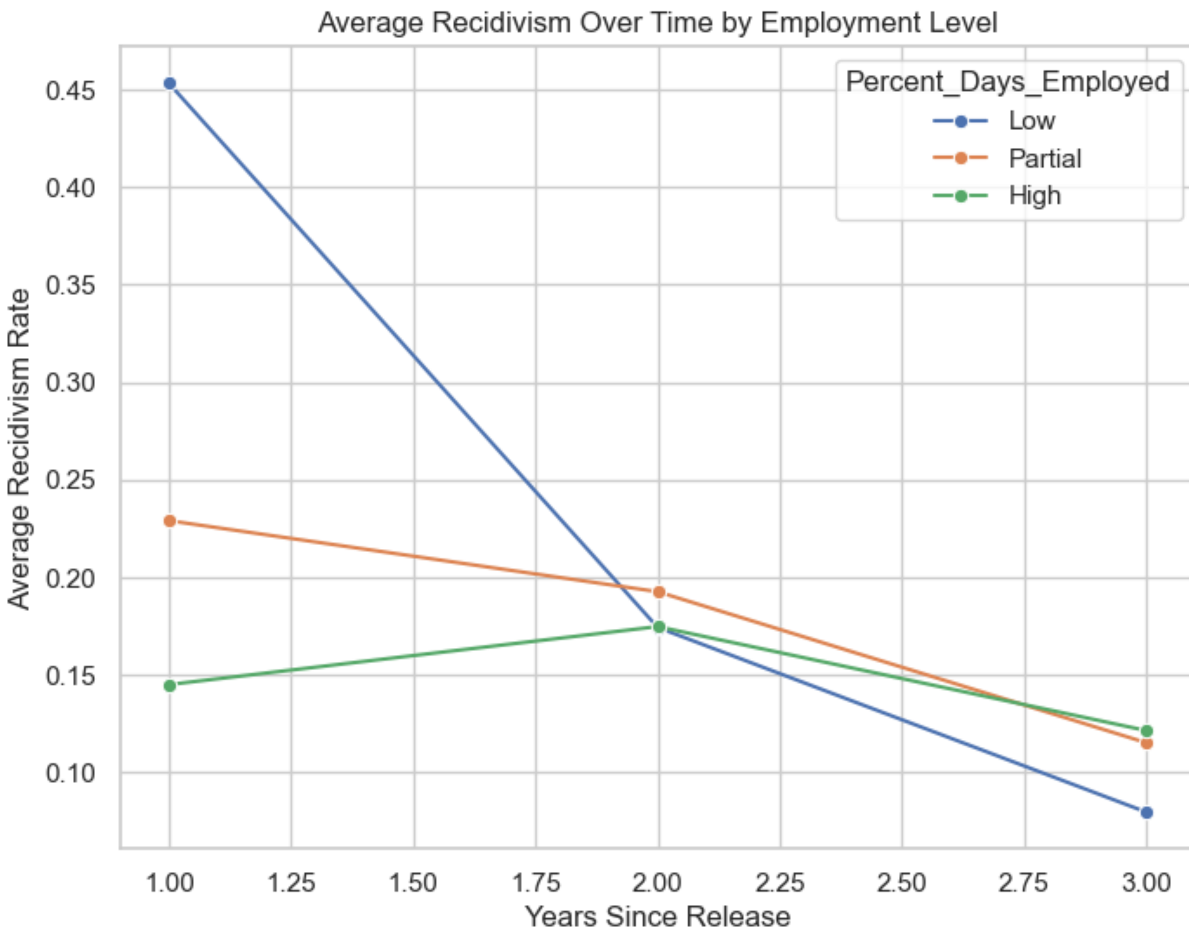
In [20]:
```
# Select only individuals who did NOT reoffend within 3 years
df_no_recid = df[df['Recidivism_Within_3years'] == False]

# Employment distribution
plt.figure(figsize=(8,6))
sns.histplot(df_no_recid['Percent_Days_Employed'], bins=10, kde=True)
plt.xlabel('Percent Days Employed')
plt.ylabel('Number of Individuals')
plt.title('Employment Distribution for Non-Recidivists')
plt.show()

# Categorize employment levels
df_no_recid['Employment_Level'] = pd.cut(
    df_no_recid['Percent_Days_Employed'],
    bins=[-0.01, 0.4, 0.7, 1],
    labels=['Low','Partial','High']
)
```




```
C:\Users\asm3886\AppData\Local\Temp\ipykernel_10708\1606978834.py:13: SettingWithCop
yWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
ser_guide/indexing.html#returning-a-view-versus-a-copy
  df_no_recid['Employment_Level'] = pd.cut(
```

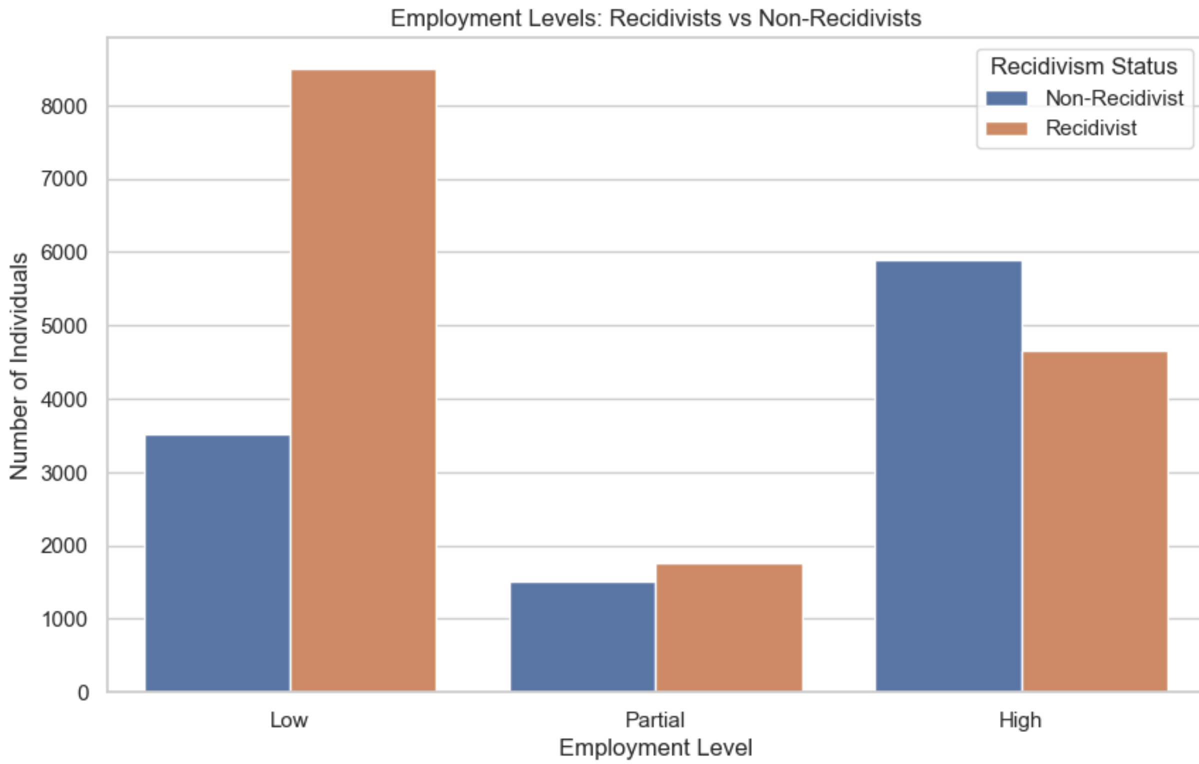
In [21]:
```
df_mean = df_long.groupby(['Year', pd.cut(df_long['Percent_Days_Employed'], bins=[-

plt.figure(figsize=(8,6))
sns.lineplot(
    x='Year',
    y='Recidivism',
    hue='Percent_Days_Employed',
    data=df_mean,
    marker='o'
)
plt.xlabel('Years Since Release')
plt.ylabel('Average Recidivism Rate')
plt.title('Average Recidivism Over Time by Employment Level')
plt.show()
```

```
C:\Users\asm3886\AppData\Local\Temp\ipykernel_10708\334640896.py:1: FutureWarning: T
he default of observed=False is deprecated and will be changed to True in a future v
ersion of pandas. Pass observed=False to retain current behavior or observed=True to
adopt the future default and silence this warning.
  df_mean = df_long.groupby(['Year', pd.cut(df_long['Percent_Days_Employed'], bins=
[-0.01,0.4,0.7,1], labels=['Low','Partial','High'])])['Recidivism'].mean().reset_ind
ex()
```



In [22]:

```python
# Categorize employment levels for the whole dataset
df['Employment_Level'] = pd.cut(
    df['Percent_Days_Employed'],
    bins=[-0.01, 0.4, 0.7, 1],
    labels=['Low','Partial','High']
)

#column for recidivism status label
df['Recidivism_Status'] = df['Recidivism_Within_3years'].map({True: 'Recidivist', F

# Plot side-by-side countplot
plt.figure(figsize=(10,6))
sns.countplot(x='Employment_Level', hue='Recidivism_Status', data=df, order=['Low',
plt.xlabel('Employment Level')
plt.ylabel('Number of Individuals')
plt.title('Employment Levels: Recidivists vs Non-Recidivists')
plt.legend(title='Recidivism Status')
plt.show()
```



In [23]:

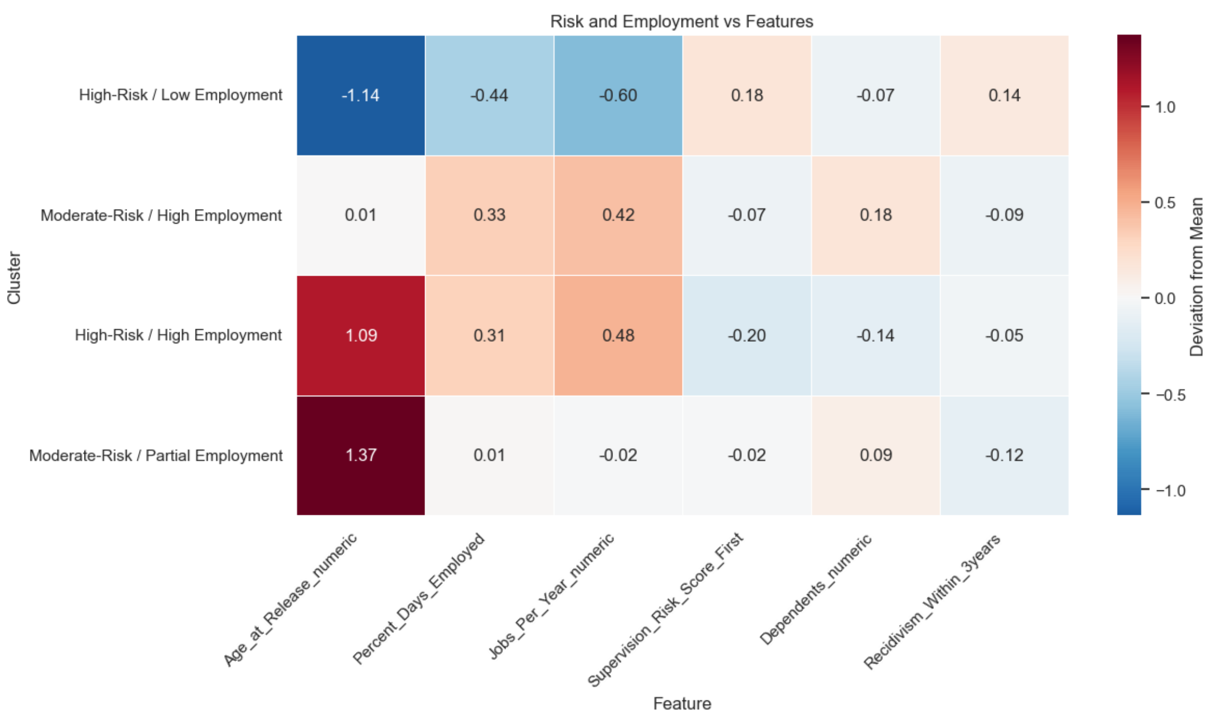
```
numeric_features = [
    'Age_at_Release_numeric',
    'Supervision_Risk_Score_First',
    'Dependents_numeric',
    'Percent_Days_Employed',
    'Jobs_Per_Year_numeric'
]

# categorical features
categorical_features = [
    'Gender',
    'Race',
    'Education_Level',
    'Supervision_Level_First',
    'Gang_Affiliated',
    'Employment_Exempt'
]

# Function to get mode of categorical feature
def mode_or_na(series):
    if series.mode().empty:
        return None
    return series.mode()[0]

# Group by cluster
cluster_summary = df.groupby('cluster').agg(
    **{f"{col}_avg": (col, 'mean') for col in numeric_features},
    **{f"{col}_mode": (col, mode_or_na) for col in categorical_features},
    Recidivism_Rate=('Recidivism_Within_3years', 'mean')
).reset_index()

# Map cluster numbers to cluster names
```

```python
if 'cluster_name' in df.columns:
    cluster_summary['cluster_name'] = cluster_summary['cluster'].map(
        df.set_index('cluster')['cluster_name'].to_dict()
    )

# Reorder columns
cols_order = ['cluster', 'cluster_name'] + \
             [f"{col}_avg" for col in numeric_features] + \
             [f"{col}_mode" for col in categorical_features] + \
             ['Recidivism_Rate']

cluster_summary = cluster_summary[cols_order]

# Display the summary
print(cluster_summary)
```

```
   cluster                        cluster_name  Age_at_Release_numeric_avg  \
0        0     Moderate-Risk / High Employment                   31.712495   
1        1         High-Risk / High Employment                   32.792531   
2        2          High-Risk / Low Employment                   30.568253   
3        3  Moderate-Risk / Partial Employment                   33.074250   

   Supervision_Risk_Score_First_avg  Dependents_numeric_avg  \
0                          6.012110                1.647386   
1                          5.877510                1.335934   
2                          6.263661                1.398816   
3                          6.063191                1.558294   

   Percent_Days_Employed_avg  Jobs_Per_Year_numeric_avg Gender_mode Race_mode  \
0                   0.807555                   1.182983           M     BLACK   
1                   0.794549                   1.242640           M     WHITE   
2                   0.045885                   0.167190           M     BLACK   
3                   0.493171                   0.747794           F     WHITE   

   Education_Level_mode Supervision_Level_First_mode Gang_Affiliated_mode  \
0   High School Diploma                     Standard                False   
1   High School Diploma                     Standard                False   
2  Less than HS diploma                     Standard                False   
3   High School Diploma                     Standard                 None   

   Employment_Exempt_mode  Recidivism_Rate  
0                   False         0.488389  
1                   False         0.527303  
2                   False         0.712445  
3                   False         0.455292  
```

In [24]:
```python
key_features = [
    'Age_at_Release_numeric',
    'Percent_Days_Employed',
    'Jobs_Per_Year_numeric',
    'Supervision_Risk_Score_First',
    'Dependents_numeric',
    'Recidivism_Within_3years'
]

#cluster means
```

```
cluster_means = df.groupby('cluster')[key_features].mean()

# Center
cluster_means_centered = cluster_means - df[key_features].mean()

if 'cluster_name' in df.columns:
    cluster_means_centered.index = df.groupby('cluster')['cluster_name'].first()

# Sort clusters by Age
cluster_means_centered = cluster_means_centered.sort_values('Age_at_Release_numeric

# Plot heatmap
plt.figure(figsize=(12,6))
sns.heatmap(
    cluster_means_centered,
    annot=True,
    cmap='RdBu_r',
    center=0,
    fmt=".2f",
    linewidths=0.5,
    cbar_kws={'label': 'Deviation from Mean'}
)
plt.title("Risk and Employment vs Features")
plt.xlabel("Feature")
plt.ylabel("Cluster")
plt.xticks(rotation=45, ha='right')
plt.show()
```



In [25]:
```
#cluster means
cleaned_csv = cluster_means.copy()

if 'cluster_name' in df.columns:
    cleaned_csv.index = df.groupby('cluster')['cluster_name'].first()
```

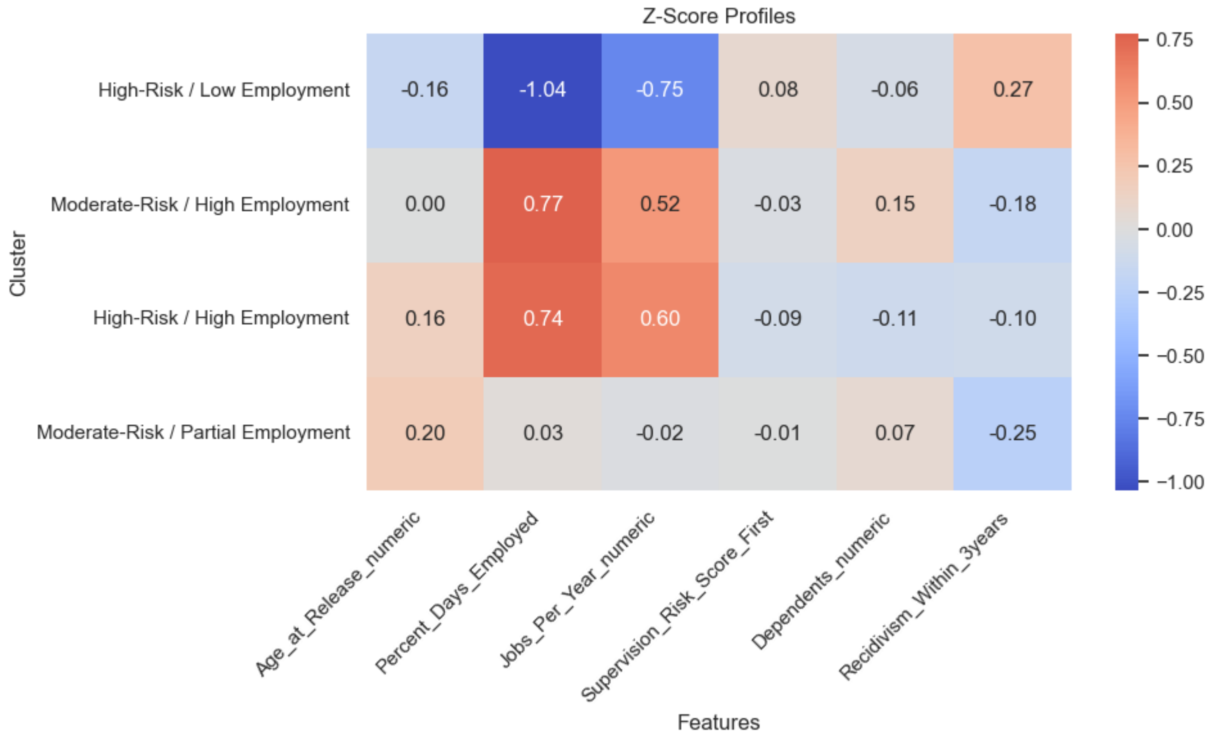
```
cleaned_csv = cleaned_csv.sort_values('Age_at_Release_numeric')
cleaned_csv
```

Out[25]:

cluster_name	Age_at_Release_numeric	Percent_Days_Employed	Jobs_Per_Year_numeric	Supe
High-Risk / Low Employment	30.568253	0.045885	0.167190	
Moderate-Risk / High Employment	31.712495	0.807555	1.182983	
High-Risk / High Employment	32.792531	0.794549	1.242640	
Moderate-Risk / Partial Employment	33.074250	0.493171	0.747794	

In [26]:

```
#Z-score normalization
df_z = df.copy()
df_z[key_features] = (df[key_features] - df[key_features].mean()) / df[key_features


#mean z-scores
cluster_std_centered = df_z.groupby('cluster')[key_features].mean()

if 'cluster_name' in df.columns:
    cluster_std_centered.index = df.groupby('cluster')['cluster_name'].first()

cluster_std_centered = cluster_std_centered.sort_values('Age_at_Release_numeric')

plt.figure(figsize=(10, 6))
sns.heatmap(
    cluster_std_centered,
    annot=True,
    cmap='coolwarm',
    center=0,
    fmt=".2f"
)

plt.title("Z-Score Profiles")
plt.xlabel("Features")
plt.ylabel("Cluster")
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



Data Interpretation

The exploratory data analysis displayed some key distribution across various features; primarily the age, employment, and dependents provided notable information about the potential for recidivism within a 3 year period. The PCA projections provided a preliminary understanding of relationships within a 2-dimensional space. The K-means clustering further discovered four distinct subgroups within the dataset. The clusters were profiled based upon a few key features: Age, percentage employed, jobs per year, supervision risk, dependents, and recidivism within 3 years. The heatmaps of these cluster groups examined the deviations from the mean populations within the data set The use of the processed z-scores allows for a cleaner comparison of the clusters across the standardized scale, and highlights how significant a deviation of the cluster may be; for example, within the dataset `High-Risk/ Low Employment` there is a notable z-score of -0.16 for `Age_at_Release` indicating a slightly younger population. Given the standardized data that was established it can be seen that the cluster with severe negative deviations of employment display higher recidivism raters, whist high employment experiences a reduced rate.

Conclusion

This data analysis demonstrates that employment is a critical protective factor that can combat recidivism. KMeans clustering, combined with Z-score normalization makes it possible to identify high-risk, low-employment subgroups that could be prioritized for intervention. Given further data such as more detailed arrrest records implementing targeted employment programs for these at-risk individuals may reduce recidivism rates and improve reintegration outcomes. These findings provide actionable insights for policymakers and rehabilitation programs, showing that data-driven clustering can reveal latent patterns to guide interventions.