Step 1: Import Required Libraries

In [1]:

```
# Importing essential libraries
import numpy as np  # For numerical operations
import pandas as pd  # For data manipulation and analysis
import matplotlib.pyplot as plt  # For data visualization
import seaborn as sns  # For enhanced visualizations
from sklearn.model_selection import train_test_split  # For splitting the dataset
from sklearn.preprocessing import LabelEncoder, StandardScaler  # For data encoding and scaling
from sklearn.decomposition import PCA  # For Principal Component Analysis
from sklearn.linear_model import LogisticRegression  # Logistic Regression model
from sklearn.metrics import accuracy_score  # For evaluating model accuracy
```

In [3]:

```
# Ignore warnings
import warnings
warnings.filterwarnings('ignore')
```

Step 2: Load and Explore the Dataset

In [6]:

```
# Load the dataset
data = pd.read_csv(r"D:\FSDS Material\Dataset\Classification\adult.csv")

# Preview the dataset
print(data.head())

# Check dataset information to identify missing values and data types
print(data.info())

# Check the shape of the dataset
print(f"Dataset contains {data.shape[0]} rows and {data.shape[1]} columns.")
```

```
   age workclass  fnlwgt     education  education.num marital.status  \
0   90         ?   77053       HS-grad              9        Widowed
1   82   Private  132870       HS-grad              9        Widowed
2   66         ?  186061  Some-college             10        Widowed
3   54   Private  140359       7th-8th              4       Divorced
4   41   Private  264663  Some-college             10      Separated

          occupation   relationship   race     sex  capital.gain  \
0                  ?  Not-in-family  White  Female             0
1    Exec-managerial  Not-in-family  White  Female             0
2                  ?      Unmarried  Black  Female             0
3  Machine-op-inspct      Unmarried  White  Female             0
4     Prof-specialty      Own-child  White  Female             0

   capital.loss  hours.per.week native.country income
0          4356              40  United-States  <=50K
1          4356              18  United-States  <=50K
2          4356              40  United-States  <=50K
3          3900              40  United-States  <=50K
4          3900              40  United-States  <=50K
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64 
 3   education       32561 non-null  object
 4   education.num   32561 non-null  int64 
 5   marital.status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital.gain    32561 non-null  int64 
 11  capital.loss    32561 non-null  int64 
 12  hours.per.week  32561 non-null  int64 
 13  native.country  32561 non-null  object
 14  income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

```
None
Dataset contains 32561 rows and 15 columns.
```

Step 3: Handle Missing Values

In [9]:
```
# Replace '?' with NaN for consistent handling of missing values
data.replace('?', np.nan, inplace=True)

# Check for missing values
print(data.isnull().sum())

# Impute missing values in categorical columns with the mode (most frequent value)
for col in ['workclass', 'occupation', 'native.country']:
    data[col] = data[col].fillna(data[col].mode()[0])  # Assign the result back to the column

# Verify no missing values remain
print(data.isnull().sum())
```

```
age                  0
workclass         1836
fnlwgt               0
education            0
education.num        0
marital.status       0
occupation        1843
relationship         0
race                 0
sex                  0
capital.gain         0
capital.loss         0
hours.per.week       0
native.country     583
income               0
dtype: int64
age               0
workclass         0
fnlwgt            0
education         0
education.num     0
marital.status    0
occupation        0
relationship      0
race              0
sex               0
capital.gain      0
capital.loss      0
hours.per.week    0
native.country    0
income            0
dtype: int64
```

In [11]:
```
data.isnull().sum()
```

Out[11]:
```
age               0
workclass         0
fnlwgt            0
education         0
education.num     0
marital.status    0
occupation        0
relationship      0
race              0
sex               0
capital.gain      0
capital.loss      0
hours.per.week    0
native.country    0
income            0
dtype: int64
```

Step 4: Set Feature Matrix (X) and Target Variable (y)

In [14]:
```
# Separate feature matrix (X) and target variable (y)
X = data.drop(['income'], axis=1)  # Drop target column from features
y = data['income']  # Target variable
```

Step 5: Split Data into Training and Test Sets

In [17]:
```
# Split the dataset into 70% training and 30% testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
```

Step 6: Encode Categorical Variables

In [20]:
```
# Encode categorical features using Label Encoding
categorical_cols = ['workclass', 'education', 'marital.status', 'occupation',
                    'relationship', 'race', 'sex', 'native.country']

le = LabelEncoder()
```

```
for col in categorical_cols:
    X_train[col] = le.fit_transform(X_train[col])
    X_test[col] = le.transform(X_test[col])
```

Step 7: Feature Scaling

In [23]:
```
# Standardize features for consistent PCA application
scaler = StandardScaler()
X_train = pd.DataFrame(scaler.fit_transform(X_train), columns=X.columns)
X_test = pd.DataFrame(scaler.transform(X_test), columns=X.columns)
```

In [25]:
```
X_train
```

Out[25]:

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex
0	0.101484	2.600478	-1.494279	-0.332263	1.133894	-0.402341	-0.782234	2.214196	0.392980	-1.430470
1	0.028248	-1.884720	0.438778	0.184396	-0.423425	-0.402341	-0.026696	-0.899410	0.392980	0.699071
2	0.247956	-0.090641	0.045292	1.217715	-0.034095	0.926666	-0.782234	-0.276689	0.392980	-1.430470
3	-0.850587	-1.884720	0.793152	0.184396	-0.423425	0.926666	-0.530388	0.968753	0.392980	0.699071
4	-0.044989	-2.781760	-0.853275	0.442726	1.523223	-0.402341	-0.782234	-0.899410	0.392980	0.699071
...	...	...	...	...	...	...	...	...	...	...
22787	3.763293	1.703439	0.870243	1.217715	-0.034095	-0.402341	-0.530388	-0.899410	0.392980	0.699071
22788	-0.191461	-0.090641	0.847831	0.184396	-0.423425	-0.402341	1.736225	-0.899410	0.392980	0.699071
22789	-0.923823	-0.090641	-1.302317	-2.140570	-0.812755	0.926666	1.232533	0.346032	-1.963453	0.699071
22790	0.394429	-0.090641	-0.704154	0.442726	1.523223	-0.402341	-0.782234	-0.899410	0.392980	0.699071
22791	0.028248	-0.090641	0.326815	0.184396	-0.423425	-0.402341	-1.034080	-0.899410	0.392980	0.699071

22792 rows × 14 columns

In [27]:
```
X_test
```

Out[27]:

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race	sex
0	1.273263	-0.090641	0.798307	-1.107252	-1.980744	2.255673	1.232533	1.591474	0.392980	-1.430470
1	-1.436476	-0.090641	0.448823	0.184396	-0.423425	0.926666	-0.278542	0.968753	0.392980	-1.430470
2	-1.143531	-0.090641	-0.608164	1.217715	-0.034095	0.926666	0.225150	-0.276689	-3.141670	-1.430470
3	-0.118225	-2.781760	-1.332357	-0.332263	1.133894	-0.402341	0.728841	-0.899410	0.392980	0.699071
4	0.760610	-0.090641	2.202540	0.442726	1.523223	-0.402341	1.232533	-0.899410	0.392980	0.699071
...	...	...	...	...	...	...	...	...	...	...
9764	-0.118225	1.703439	-1.518569	0.184396	-0.423425	-0.402341	-0.530388	-0.899410	0.392980	0.699071
9765	-0.923823	-0.090641	-0.228829	0.184396	-0.423425	-0.402341	1.232533	-0.899410	0.392980	0.699071
9766	-0.997059	-0.090641	-0.312141	1.217715	-0.034095	0.926666	0.728841	0.968753	0.392980	0.699071
9767	-0.337933	-0.090641	-0.393536	0.184396	-0.423425	0.926666	-0.026696	1.591474	-1.963453	-1.430470
9768	0.833846	-0.090641	-0.901761	-0.590592	0.355234	-0.402341	-1.034080	-0.899410	0.392980	0.699071

9769 rows × 14 columns

Step 8: Train Logistic Regression with All Features

In [28]:
```
# Train Logistic Regression model on all features
logreg = LogisticRegression()
logreg.fit(X_train, y_train)

# Make predictions on the test set
y_pred = logreg.predict(X_test)

# Calculate accuracy
print(f"Logistic Regression Accuracy (All Features): {accuracy_score(y_test, y_pred):.4f}".format(accuracy_score(y_te
```

```
Logistic Regression Accuracy (All Features): 0.8218
```

Step 9: Apply PCA for Dimensionality Reduction

In [36]:
```python
# Apply PCA to reduce dimensionality
pca = PCA()
X_train_pca = pca.fit_transform(X_train)
X_test_pca = pca.transform(X_test)

# Explained variance ratio for each principal component
print("Explained Variance Ratio:", pca.explained_variance_ratio_)

# Calculate cumulative explained variance
cumulative_variance = np.cumsum(pca.explained_variance_ratio_)
print("Cumulative Explained Variance:", cumulative_variance)
```

```
Explained Variance Ratio: [0.14757168 0.10182915 0.08147199 0.07880174 0.07463545 0.07274281
 0.07009602 0.06750902 0.0647268  0.06131155 0.06084207 0.04839584
 0.04265038 0.02741548]
Cumulative Explained Variance: [0.14757168 0.24940083 0.33087282 0.40967457 0.48431002 0.55705283
 0.62714886 0.69465787 0.75938468 0.82069623 0.8815383  0.92993414
 0.97258452 1.        ]
```

Step 10: Determine Optimal Number of Dimensions

In [38]:
```python
# Find the number of components to preserve 90% of variance
optimal_dims = np.argmax(cumulative_variance >= 0.90) + 1
print(f"Number of components to preserve 90% variance: {optimal_dims}")

# Apply PCA with the optimal number of components
pca_optimal = PCA(n_components=optimal_dims)
X_train_pca = pca_optimal.fit_transform(X_train)
X_test_pca = pca_optimal.transform(X_test)
```

```
Number of components to preserve 90% variance: 12
```

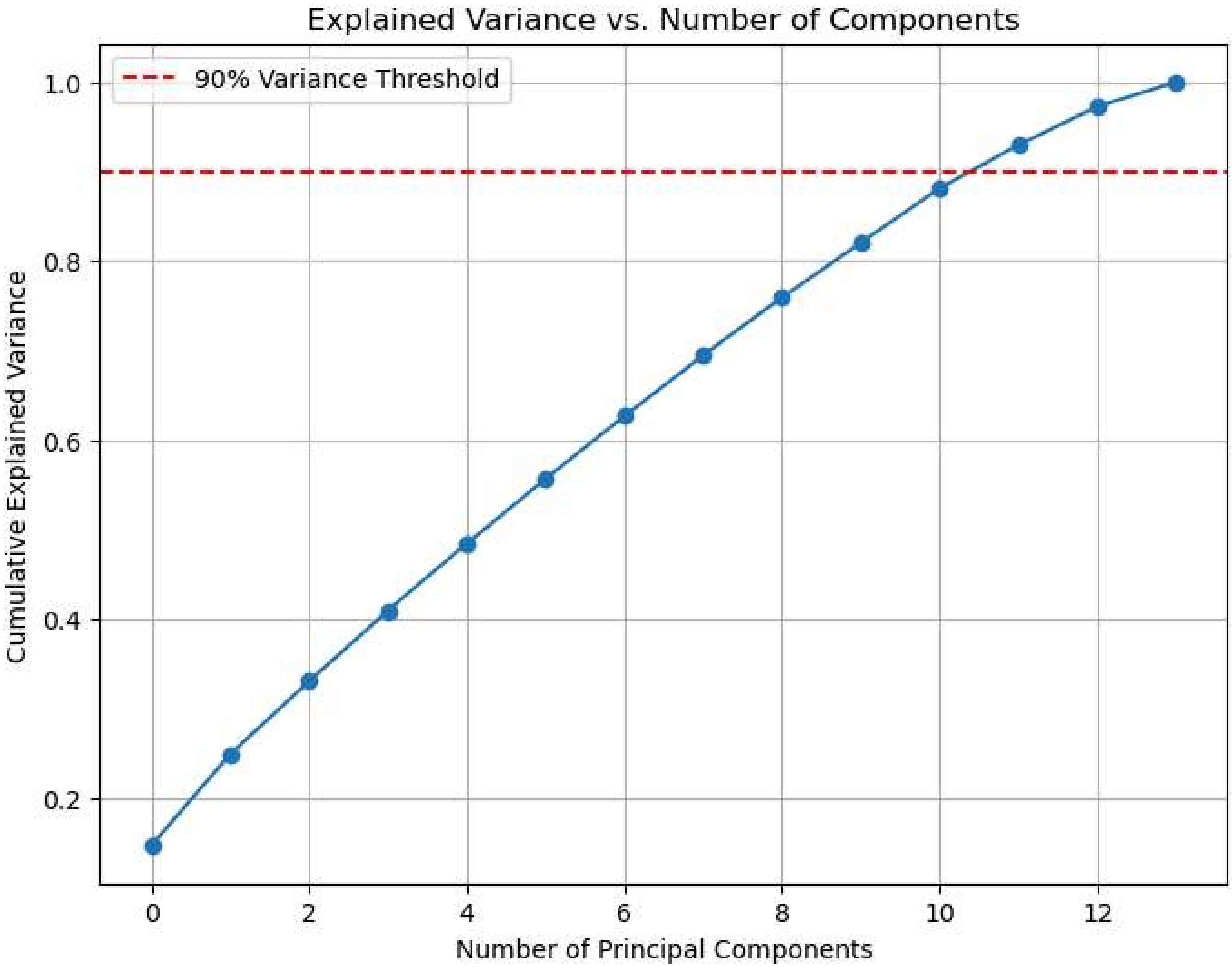
Step 11: Train Logistic Regression with Reduced Features

In [49]:
```
# Train Logistic Regression with PCA-transformed features
logreg_pca = LogisticRegression()
logreg_pca.fit(X_train_pca, y_train)

# Make predictions
y_pred_pca = logreg_pca.predict(X_test_pca)

# Calculate accuracy
print(f"Logistic Regression Accuracy (PCA Features): {accuracy_score(y_test, y_pred_pca):.4f}")
```

```
Logistic Regression Accuracy (PCA Features): 0.8209
```

Step 12: Plot Explained Variance Ratio

In [45]:
```
# Visualize cumulative explained variance
plt.figure(figsize=(8, 6))
plt.plot(cumulative_variance, marker='o')
plt.axhline(y=0.90, color='r', linestyle='--', label='90% Variance Threshold')
plt.xlabel('Number of Principal Components')
plt.ylabel('Cumulative Explained Variance')
plt.title('Explained Variance vs. Number of Components')
plt.legend()
plt.grid()
plt.show()
```


Explained Variance vs. Number of Components
90% Variance Threshold
1.0
0.8
0.6
0.4
0.2
Cumulative Explained Variance
0
2
4
6
8
10
12
Number of Principal Components

In [ ]: