Case Study_Human Resourse Dataset

- **Human_Resources.csv Analysis**
- Apply K mean Clustering
- Apply PCA
- Apply Autoencoder

Task 1:Import your libraries (Lab 2)

In [3]:
```
#Import the libraries here
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
```

In [4]:
```
#Attach the Human_Resource.csv file and view the first five records
df = pd.read_csv('Human_Resources.csv')
df.head()
```

Out[4]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeN
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	
1	49	No	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	Other	1	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	
4	27	No	Travel_Rarely	591	Research & Development	2	1	Medical	1	

5 rows × 35 columns

In [5]:
```
# show all the file data types
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 35 columns):
 #   Column                    Non-Null Count  Dtype 
---  ------                    --------------  ----- 
 0   Age                       1470 non-null   int64 
 1   Attrition                 1470 non-null   object
 2   BusinessTravel            1470 non-null   object
 3   DailyRate                 1470 non-null   int64 
 4   Department                1470 non-null   object
 5   DistanceFromHome          1470 non-null   int64 
 6   Education                 1470 non-null   int64 
 7   EducationField            1470 non-null   object
 8   EmployeeCount             1470 non-null   int64 
 9   EmployeeNumber            1470 non-null   int64 
 10  EnvironmentSatisfaction   1470 non-null   int64 
 11  Gender                    1470 non-null   object
 12  HourlyRate                1470 non-null   int64 
 13  JobInvolvement            1470 non-null   int64 
 14  JobLevel                  1470 non-null   int64 
 15  JobRole                   1470 non-null   object
 16  JobSatisfaction           1470 non-null   int64 
 17  MaritalStatus             1470 non-null   object
 18  MonthlyIncome             1470 non-null   int64 
 19  MonthlyRate               1470 non-null   int64 
 20  NumCompaniesWorked        1470 non-null   int64 
 21  Over18                    1470 non-null   object
 22  OverTime                  1470 non-null   object
 23  PercentSalaryHike         1470 non-null   int64 
 24  PerformanceRating         1470 non-null   int64 
 25  RelationshipSatisfaction  1470 non-null   int64 
 26  StandardHours             1470 non-null   int64 
 27  StockOptionLevel          1470 non-null   int64 
 28  TotalWorkingYears         1470 non-null   int64 
 29  TrainingTimesLastYear     1470 non-null   int64 
 30  WorkLifeBalance           1470 non-null   int64 
 31  YearsAtCompany            1470 non-null   int64 
 32  YearsInCurrentRole        1470 non-null   int64 
 33  YearsSinceLastPromotion   1470 non-null   int64 
 34  YearsWithCurrManager      1470 non-null   int64 
dtypes: int64(26), object(9)
memory usage: 402.1+ KB
```

In [6]:
```
# Show the following basic statistics
df.describe()
```

Out[6]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	EnvironmentSatisfaction	Hour
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.0	1470.000000	1470.000000	1470.0
mean	36.923810	802.485714	9.192517	2.912925	1.0	1024.865306	2.721769	65.8
std	9.135373	403.509100	8.106864	1.024165	0.0	602.024335	1.093082	20.3
min	18.000000	102.000000	1.000000	1.000000	1.0	1.000000	1.000000	30.0
25%	30.000000	465.000000	2.000000	2.000000	1.0	491.250000	2.000000	48.0
50%	36.000000	802.000000	7.000000	3.000000	1.0	1020.500000	3.000000	66.0
75%	43.000000	1157.000000	14.000000	4.000000	1.0	1555.750000	4.000000	83.7
max	60.000000	1499.000000	29.000000	5.000000	1.0	2068.000000	4.000000	100.0

8 rows × 26 columns

Task 2: Visualize Dataset (Lab 2)

In [8]:
```
# Replace 'Attritition','Overtime' and 'Over18' columns with integers before performing any visualizations
df['Attrition'] = df['Attrition'].map({'Yes': 1, 'No': 0})
df['OverTime'] = df['OverTime'].map({'Yes': 1, 'No': 0})
df['Over18'] = df['Over18'].map({'Y': 1})
```

In [9]:
```
# display the current first four records
df.head(4)
```

Out[9]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	EducationField	EmployeeCount	EmployeeN
0	41	1	Travel_Rarely	1102	Sales	1	2	Life Sciences	1	
1	49	0	Travel_Frequently	279	Research & Development	8	1	Life Sciences	1	
2	37	1	Travel_Rarely	1373	Research & Development	2	2	Other	1	
3	33	0	Travel_Frequently	1392	Research & Development	3	4	Life Sciences	1	

4 rows × 35 columns

In [10]:

```
# Drop EmployeeNumber',EmployeeCount' ,'Standardhours' and 'Over18' since they do not change from one employee to the o
df.drop(['EmployeeNumber', 'EmployeeCount', 'StandardHours', 'Over18'], axis=1, inplace=True)
```

In [11]:

```
# Let's see how many employees left the company!
left_df        = df[df['Attrition'] == 1]
stayed_df      = df[df['Attrition'] == 0]
```

In [12]:

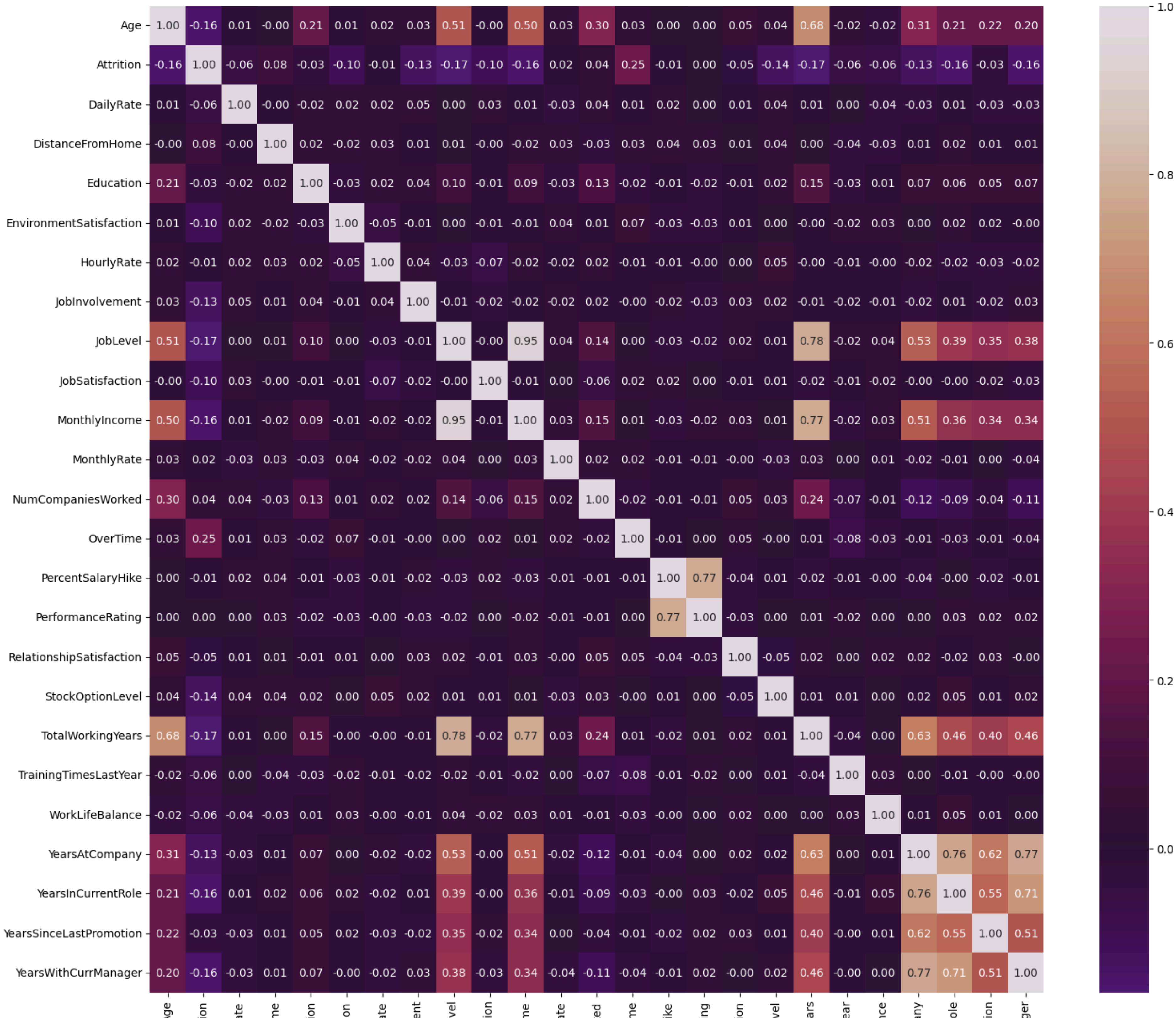
```
# Count the number of employees who stayed and left
# It seems that we are dealing with an imbalanced dataset
total = len(df)

num_left = len(left_df)
pct_left = (num_left / total) * 100

num_stayed = len(stayed_df)
pct_stayed = (num_stayed / total) * 100

print(f"Total = {total}")
print(f"Number of employees who left the company = {num_left}")
print(f"Percentage of employees who left the company = {pct_left} %")
print(f"Number of employees who did not leave the company (stayed) = {num_stayed}")
print(f"Percentage of employees who did not leave the company (stayed) = {pct_stayed} %")
```

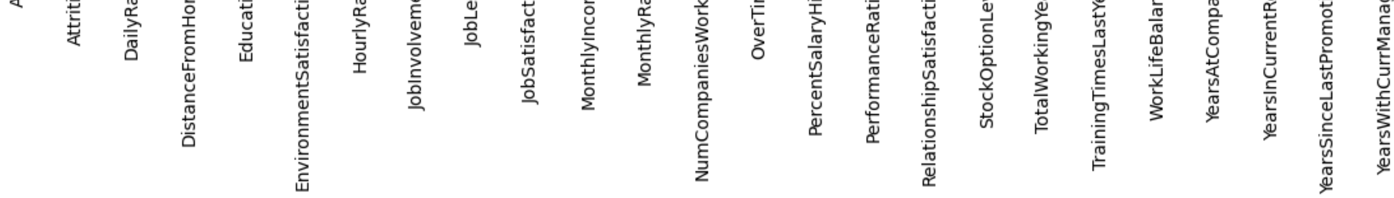
```
Total = 1470
Number of employees who left the company = 237
Percentage of employees who left the company = 16.122448979591837 %
Number of employees who did not leave the company (stayed) = 1233
Percentage of employees who did not leave the company (stayed) = 83.87755102040816 %
```

In [13]:

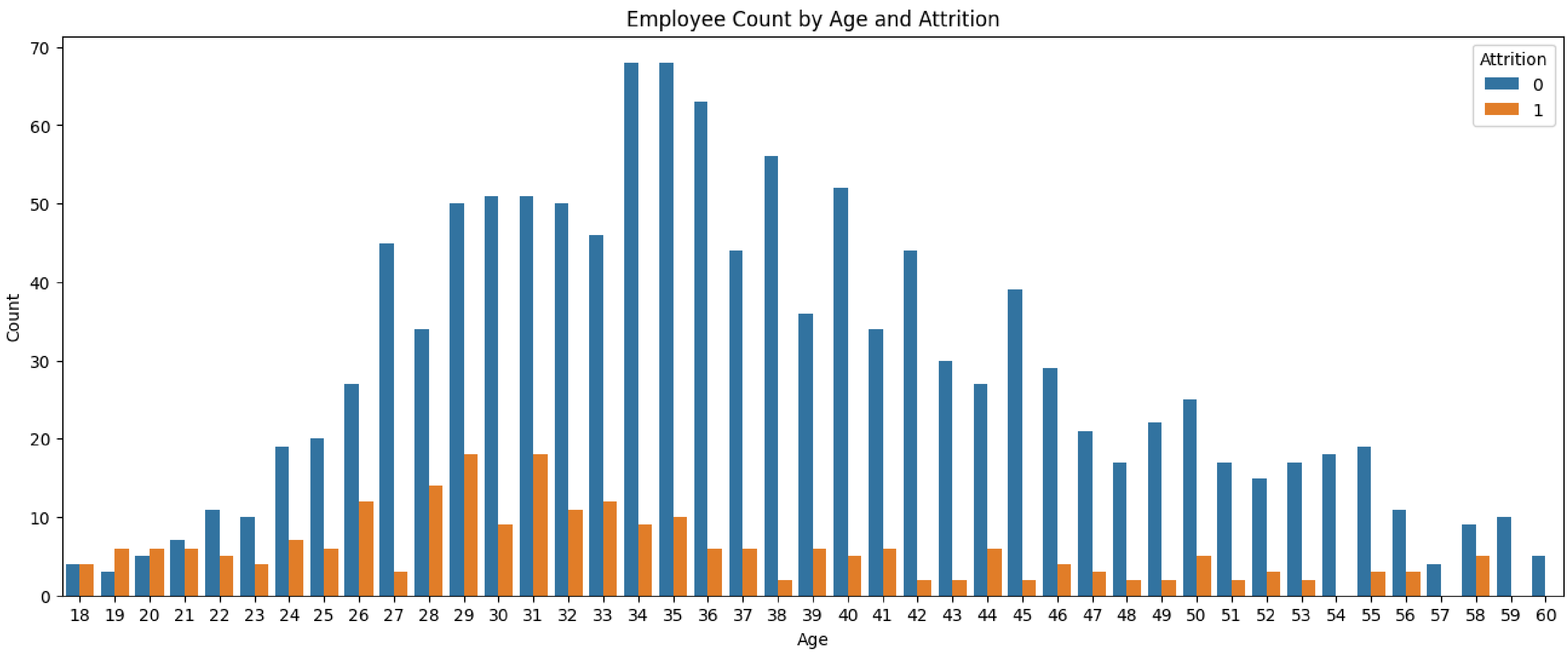
```
# show the correlation heat map as below
plt.figure(figsize=(18, 16))
```

```python
corr = df.corr(numeric_only=True)
sns.heatmap(corr, annot=True, fmt=".2f", cmap='twilight', center=0)
plt.show()
```


Age
Attrition
DailyRate
DistanceFromHome
Education
EnvironmentSatisfaction
HourlyRate
JobInvolvement
JobLevel
JobSatisfaction
MonthlyIncome
MonthlyRate
NumCompaniesWorked
OverTime
PercentSalaryHike
PerformanceRating
RelationshipSatisfaction
StockOptionLevel
TotalWorkingYears
TrainingTimesLastYear
WorkLifeBalance
YearsAtCompany
YearsInCurrentRole
YearsSinceLastPromotion
YearsWithCurrManager
1.0
0.8
0.6
0.4
0.2
0.0

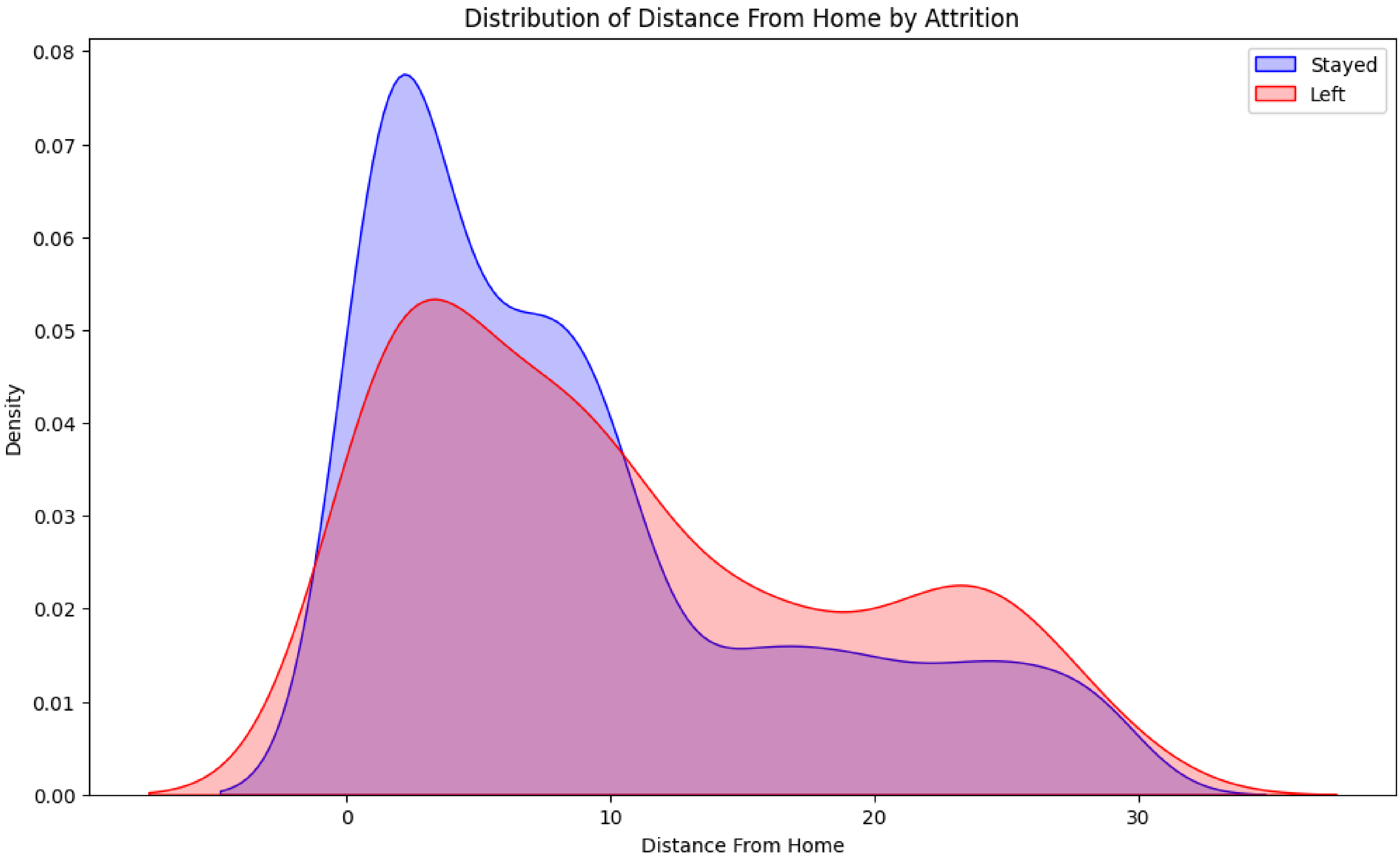


In [14]:
```python
# Display the below visualization with hue as Attrition
plt.figure(figsize=(16, 6))

sns.countplot(data=df, x='Age', hue='Attrition')

plt.xlabel('Age')
plt.ylabel('Count')
plt.title('Employee Count by Age and Attrition')
plt.show()
```



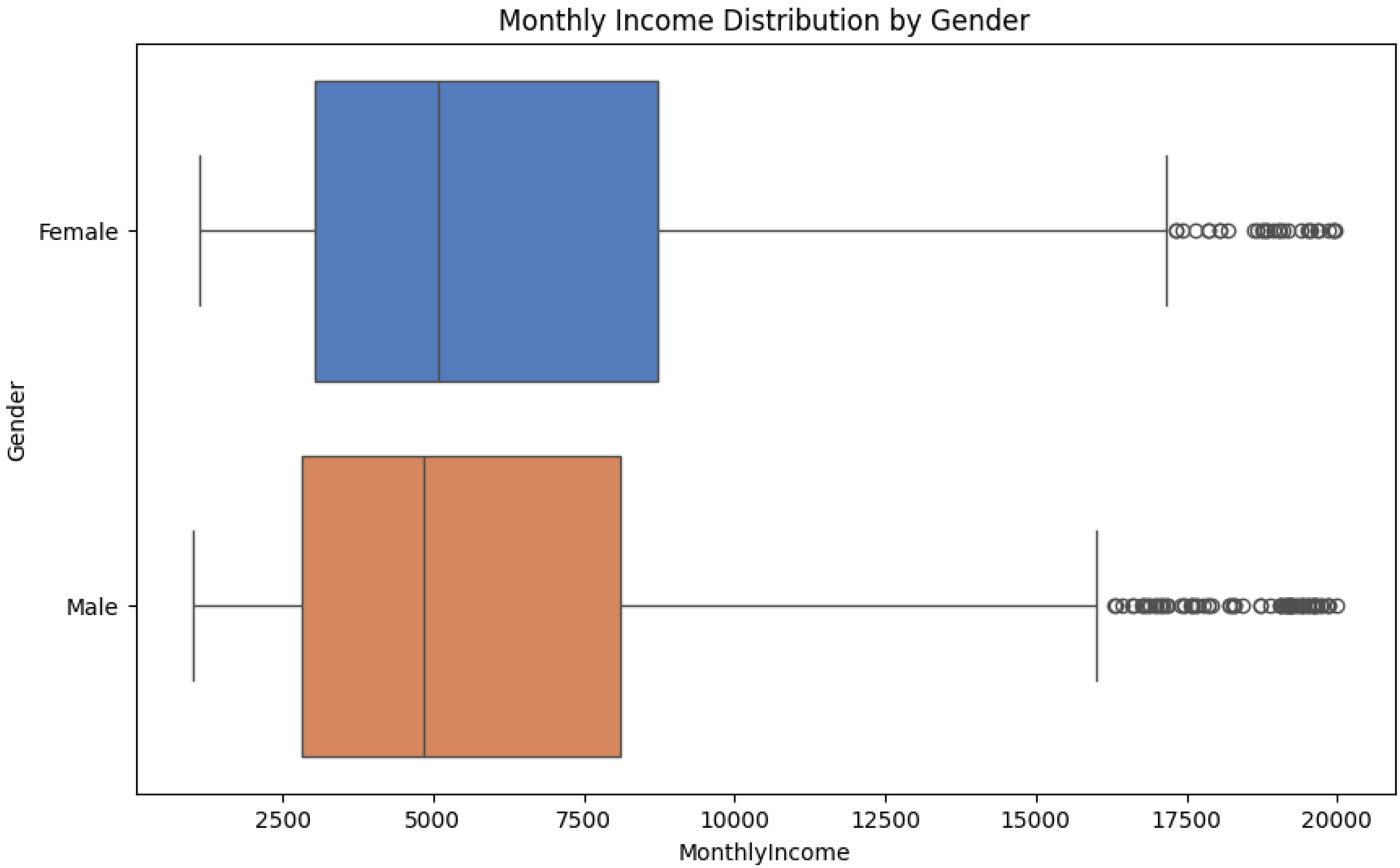
In [15]:
```python
# create a Kernel Density Estimate comparing 'Employees who left' and 'Employees who Stayed' using 'Distance From Home'
plt.figure(figsize=(12,7))
sns.kdeplot(df[df['Attrition'] == 0]['DistanceFromHome'], color='blue', fill=True, label='Stayed')

sns.kdeplot(df[df['Attrition'] == 1]['DistanceFromHome'], color='red', fill=True, label='Left')
```

```
plt.title('Distribution of Distance From Home by Attrition')
plt.xlabel('Distance From Home')
plt.ylabel('Density')
plt.legend()
plt.show()
```



In [16]:
```
# Let's see the Gender vs. Monthly Income using box plots
plt.figure(figsize=(10, 6))

sns.boxplot(data=df, x='MonthlyIncome', y='Gender', hue='Gender', palette='muted', dodge=False)
plt.title('Monthly Income Distribution by Gender')
plt.xlabel('MonthlyIncome')
```

```
plt.ylabel('Gender')
plt.show()
```



Task 3: Create Testing and Training Dataset & Perform Data Cleaning (Lab 2)

In [18]:
```
# Convert the categorical fields into numerics using OneHotEncoder
categorical_cols = df.select_dtypes(include='object').columns.tolist()

encoder = OneHotEncoder(drop='first', sparse_output=False)

encoded_array = encoder.fit_transform(df[categorical_cols])

encoded_df = pd.DataFrame(encoded_array, columns=encoder.get_feature_names_out(categorical_cols))
```

```python
df_encoded = pd.concat([df.drop(columns=categorical_cols).reset_index(drop=True), encoded_df], axis=1)
```

In [19]:
```python
# select your features here i.e. drop the target 'Atrittion'
X = df_encoded.drop(columns=['Attrition'])

X
```

Out[19]:

	Age	DailyRate	DistanceFromHome	Education	EnvironmentSatisfaction	HourlyRate	JobInvolvement	JobLevel	JobSatisfaction
0	41	1102	1	2	2	94	3	2	4
1	49	279	8	1	3	61	2	2	2
2	37	1373	2	2	4	92	2	1	3
3	33	1392	3	4	4	56	3	1	3
4	27	591	2	1	1	40	3	1	2
...	...	...	...	...	...	...	...	...	...
1465	36	884	23	2	3	41	4	2	4
1466	39	613	6	1	4	42	2	3	1
1467	27	155	4	3	2	87	4	2	2
1468	49	1023	2	3	4	63	2	2	2
1469	34	628	8	3	2	82	4	2	3

1470 rows × 44 columns

In [20]:
```python
# scale your features data assigning it variable X
scaler = StandardScaler()
X = scaler.fit_transform(X)
```

In [21]:
```python
X
```

Out[21]:
```
array([[ 0.4463504 ,  0.74252653, -1.01090934, ..., -0.24462499,
        -0.91892141,  1.45864991],
       [ 1.32236521, -1.2977746 , -0.14714972, ..., -0.24462499,
         1.08823234, -0.68556546],
       [ 0.008343  ,  1.41436324, -0.88751511, ..., -0.24462499,
        -0.91892141,  1.45864991],
       ...,
       [-1.08667552, -1.60518328, -0.64072665, ..., -0.24462499,
         1.08823234, -0.68556546],
       [ 1.32236521,  0.54667746, -0.88751511, ..., -0.24462499,
         1.08823234, -0.68556546],
       [-0.32016256, -0.43256792, -0.14714972, ..., -0.24462499,
         1.08823234, -0.68556546]])
```

In [22]:
```
# select your dependent, target or response data as "Attrition" using variable y
y = df_encoded['Attrition']
```

In [23]:
```
y
```

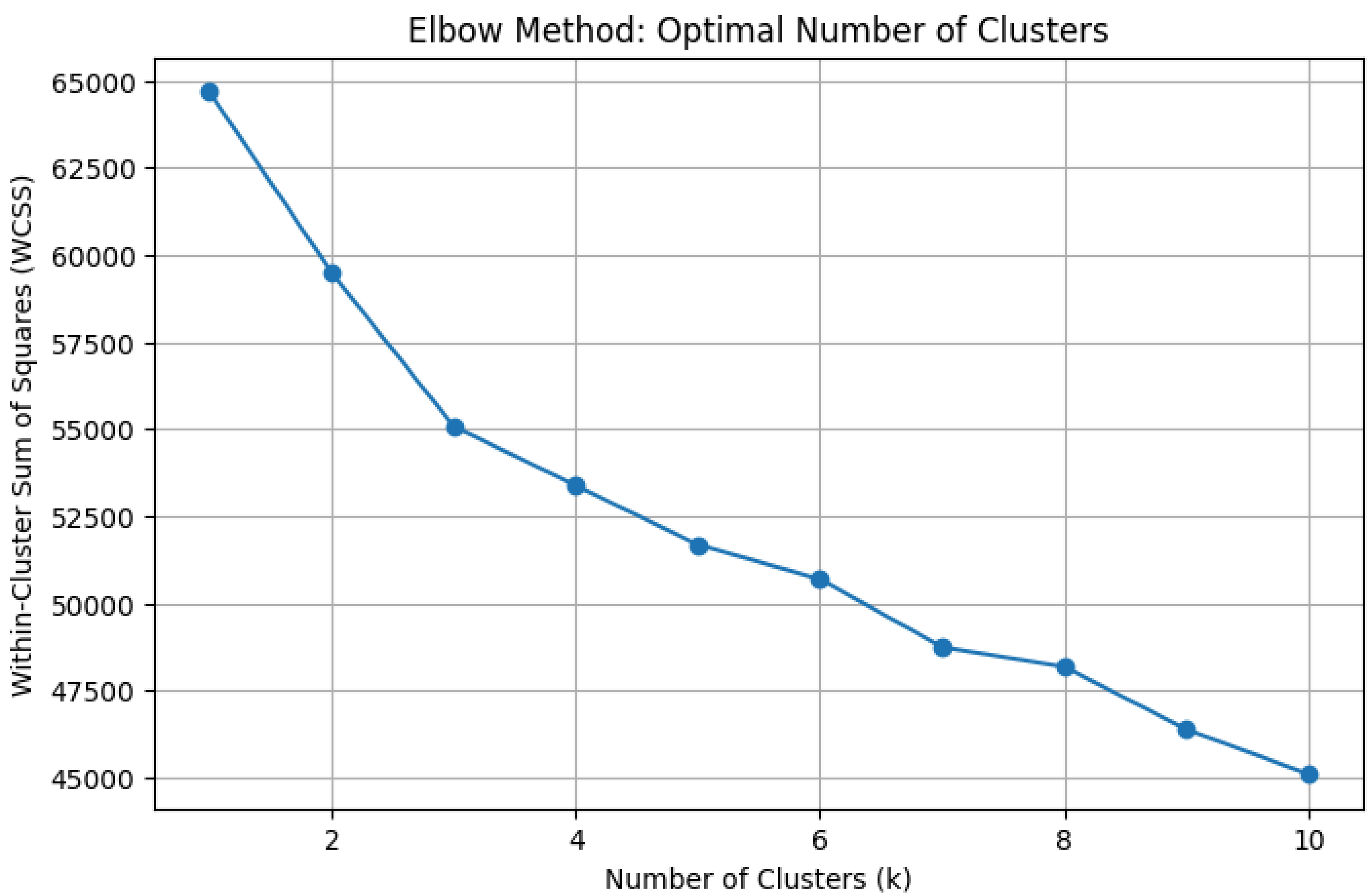
Out[23]:
```
0       1
1       0
2       1
3       0
4       0
       ..
1465    0
1466    0
1467    0
1468    0
1469    0
Name: Attrition, Length: 1470, dtype: int64
```

Task 4: Find the Optimal Number of Clusters using Elblow Method (Lab 2)

In [25]:
```
# Compute 'within cluster sum of squares' or WCSS metric for a range of k clusters
wcss = []

for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, init='k-means++', random_state=5503)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)
```

In [26]:
```
# Create a visualization for Finding the right number of clusters - Elbow method'
plt.figure(figsize=(8, 5))
plt.plot(range(1, 11), wcss, marker='o')
```

```
plt.title('Elbow Method: Optimal Number of Clusters')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Within-Cluster Sum of Squares (WCSS)')
plt.grid(True)
plt.show()
```



Task 5: Apply K-Means Clustering (Lab 2)

In [28]:
```
optimal_k = 3
```

In [29]:
```
kmeans = KMeans(n_clusters=optimal_k, init='k-means++', random_state=5503)
y_kmeans = kmeans.fit_predict(X)
```

In [30]:
```
unique, counts = np.unique(y_kmeans, return_counts=True)
```

In [31]:
```
# Check size of each cluster - Are they all representative ?
```

In [32]:
```
for cluster, size in zip(unique, counts):
    print(f"Cluster {cluster}: {size} points")
```

```
Cluster 0: 251 points
Cluster 1: 399 points
Cluster 2: 820 points
```

Are they all representative ?

- Cluster 0: 251 points
- Cluster 1: 399 points
- Cluster 2: 820 points

All clusters contain a substantial number of data points. Therefore, all the clusters are considered representative of the dataset.

Task 6: Apply PCA and Visualize Results (Lab 3)

In [35]:
```
# Obtain the principal components
pca = PCA()
X_pca = pca.fit_transform(X)
```

In [36]:
```
# All samples projected on the two principal components
pca = PCA(n_components=2)
X_pca_2d = pca.fit_transform(X)
```

In [37]:
```
# Create a dataframe with the two components
pca_df = pd.DataFrame(X_pca_2d, columns=['PC1', 'PC2'])
```

In [38]:
```
# Concatenate the clusters labels to the dataframe
pca_df['Cluster'] = y_kmeans
```

In [39]:
```
pca_df.head()
```

Out[39]:

	PC1	PC2	Cluster
0	-0.034512	2.271801	1
1	0.097444	-1.569353	2
2	-2.871946	-0.993176	2
3	-1.222608	-1.126880	2
4	-2.075628	-1.211932	2

In [ ]:

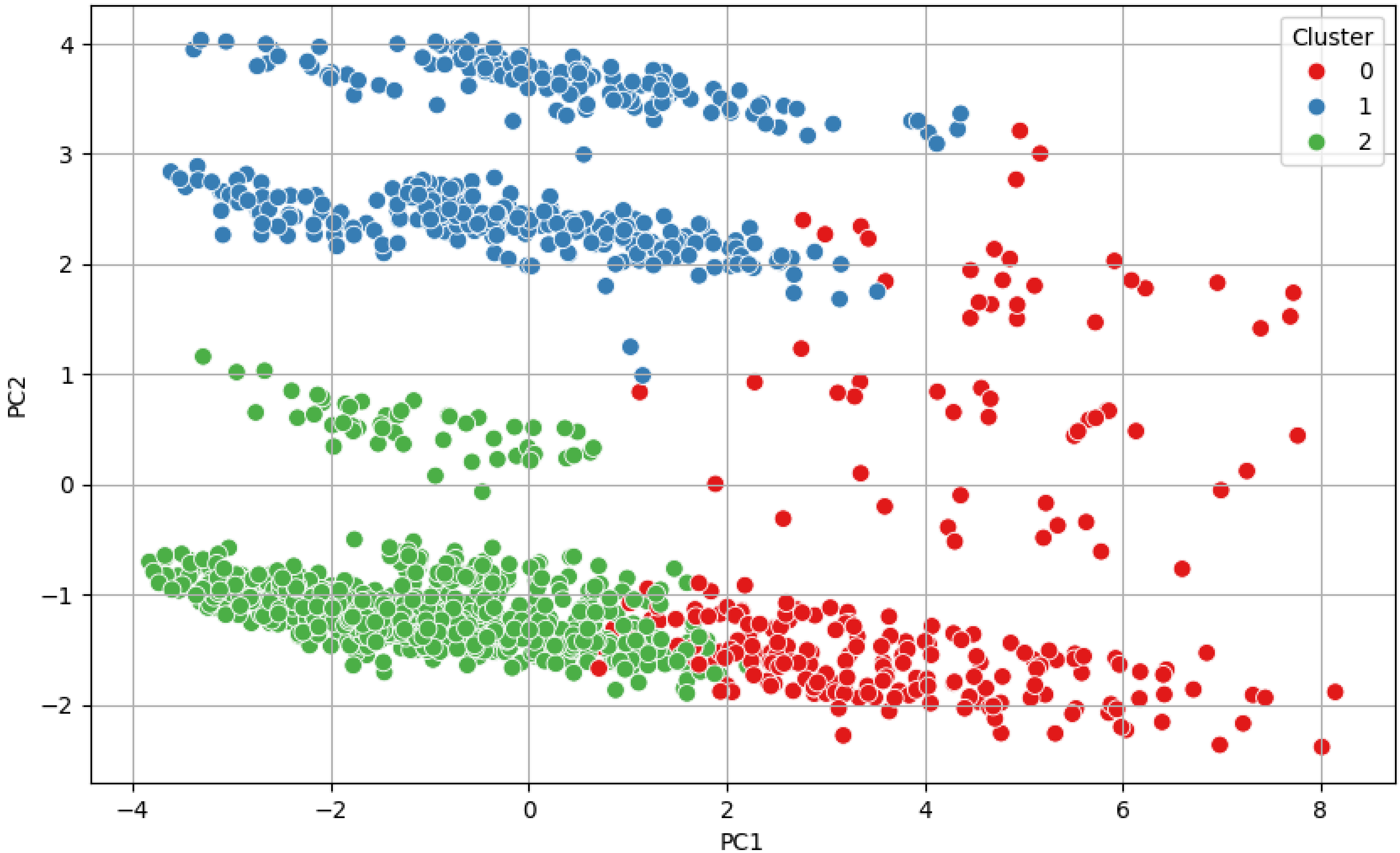
```

```

In [ ]:

```

```

In [40]:

```
# Create a scatterplot visual of Projection of the dataset on the 2 PCA dimensions'
plt.figure(figsize=(10, 6))

sns.scatterplot(data=pca_df, x='PC1', y='PC2', hue='Cluster', palette='Set1', s=60)
plt.legend(title='Cluster')
plt.grid(True)
plt.show()
```



In [41]:
```
# show the % of the total variance explained by each principal component. Overall close to 48% explained by these two.
explained_var = pca.explained_variance_ratio_
print(f"PC1 explains: {explained_var[0] * 100:.2f}% of variance")
print(f"PC2 explains: {explained_var[1] * 100:.2f}% of variance")
print(f"Total variance explained by first 2 PCs: {explained_var[:2].sum() * 100:.2f}%")
```

```
PC1 explains: 12.13% of variance
PC2 explains: 7.85% of variance
Total variance explained by first 2 PCs: 19.98%
```

Task 7: Perform Dimensionality Reduction using Autoencoders (Lab 3)

In [43]:
```
#import the autoencoder libraries
import tensorflow as tf
```

```python
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense
from tensorflow.keras.optimizers import Adam
```

```
2025-05-25 01:25:59.323727: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to
use available CPU instructions in performance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler f
lags.
```

In [44]:
```python
# create your autoencoder with all the features showing Encoder, bottleneck, decoder, autoencoder
# compile the autoencoder using optimizer='adam', loss='mean_squared_error'


# Input diamention
input_dim = X.shape[1]

# Encoder
input_layer = Input(shape=(input_dim,))
encoded = Dense(32, activation='relu')(input_layer)
encoded = Dense(16, activation='relu')(encoded)

# Bottleneck
bottleneck = Dense(8, activation='relu')(encoded)

# Decoder
decoded = Dense(16, activation='relu')(bottleneck)
decoded = Dense(32, activation='relu')(decoded)
output_layer = Dense(input_dim, activation='linear')(decoded)

# Autoencoder
autoencoder = Model(inputs=input_layer, outputs=output_layer)

# Compile the autoencoder
autoencoder.compile(optimizer='adam', loss='mean_squared_error')
```

In [45]:
```python
# show the autoencoder summary
autoencoder.summary()
```

Model: "functional"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 44)	0
dense (Dense)	(None, 32)	1,440
dense_1 (Dense)	(None, 16)	528
dense_2 (Dense)	(None, 8)	136
dense_3 (Dense)	(None, 16)	144
dense_4 (Dense)	(None, 32)	544
dense_5 (Dense)	(None, 44)	1,452

Total params: 4,244 (16.58 KB)

Trainable params: 4,244 (16.58 KB)

Non-trainable params: 0 (0.00 B)

In [46]:

```
## Train autoencoder using input = output
history = autoencoder.fit(
    X, X,
    epochs=50,
    batch_size=32,
    shuffle=True,
    validation_split=0.2
)
```

```
Epoch 1/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - loss: 1.0132 - val_loss: 0.9672
Epoch 2/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.9896 - val_loss: 0.9307
Epoch 3/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.9290 - val_loss: 0.8809
Epoch 4/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.8669 - val_loss: 0.8295
Epoch 5/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.8258 - val_loss: 0.7863
Epoch 6/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.7702 - val_loss: 0.7622
Epoch 7/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.7438 - val_loss: 0.7468
Epoch 8/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.7344 - val_loss: 0.7338
Epoch 9/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.7351 - val_loss: 0.7196
Epoch 10/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.7126 - val_loss: 0.7073
Epoch 11/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.6996 - val_loss: 0.6950
Epoch 12/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.6833 - val_loss: 0.6815
Epoch 13/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step - loss: 0.6689 - val_loss: 0.6710
Epoch 14/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.6606 - val_loss: 0.6613
Epoch 15/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.6444 - val_loss: 0.6517
Epoch 16/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.6458 - val_loss: 0.6429
Epoch 17/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.6322 - val_loss: 0.6332
Epoch 18/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.6236 - val_loss: 0.6231
Epoch 19/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.6159 - val_loss: 0.6159
Epoch 20/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.6151 - val_loss: 0.6068
Epoch 21/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.6036 - val_loss: 0.5992
Epoch 22/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.5900 - val_loss: 0.5922
Epoch 23/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5903 - val_loss: 0.5870
Epoch 24/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5817 - val_loss: 0.5799
```

```
Epoch 25/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5826 - val_loss: 0.5750
Epoch 26/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5747 - val_loss: 0.5724
Epoch 27/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5622 - val_loss: 0.5659
Epoch 28/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5674 - val_loss: 0.5607
Epoch 29/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.5500 - val_loss: 0.5580
Epoch 30/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.5590 - val_loss: 0.5529
Epoch 31/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5495 - val_loss: 0.5476
Epoch 32/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5463 - val_loss: 0.5456
Epoch 33/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5419 - val_loss: 0.5428
Epoch 34/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5378 - val_loss: 0.5381
Epoch 35/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5275 - val_loss: 0.5334
Epoch 36/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.5349 - val_loss: 0.5338
Epoch 37/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5252 - val_loss: 0.5277
Epoch 38/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.5156 - val_loss: 0.5246
Epoch 39/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5239 - val_loss: 0.5220
Epoch 40/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5162 - val_loss: 0.5193
Epoch 41/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.5070 - val_loss: 0.5181
Epoch 42/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.5104 - val_loss: 0.5143
Epoch 43/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 4ms/step - loss: 0.5106 - val_loss: 0.5146
Epoch 44/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5047 - val_loss: 0.5116
Epoch 45/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5046 - val_loss: 0.5092
Epoch 46/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.5024 - val_loss: 0.5104
Epoch 47/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.4939 - val_loss: 0.5047
Epoch 48/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.4846 - val_loss: 0.5038
```

```
Epoch 49/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.4957 - val_loss: 0.5018
Epoch 50/50
37/37 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.4959 - val_loss: 0.5022
```

In [47]:

```
# Use Autoencoder to reduce the number of features / dimensions and show the dimensions
encoder = Model(inputs=autoencoder.input, outputs=autoencoder.get_layer(index=3).output)

X_encoded = encoder.predict(X)

print("Original shape:", X.shape)
print("Reduced shape:", X_encoded.shape)
```

```
46/46 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step
Original shape: (1470, 44)
Reduced shape: (1470, 8)
```

Task 8: Apply KMEANS to encoded dataset (Lab 3)

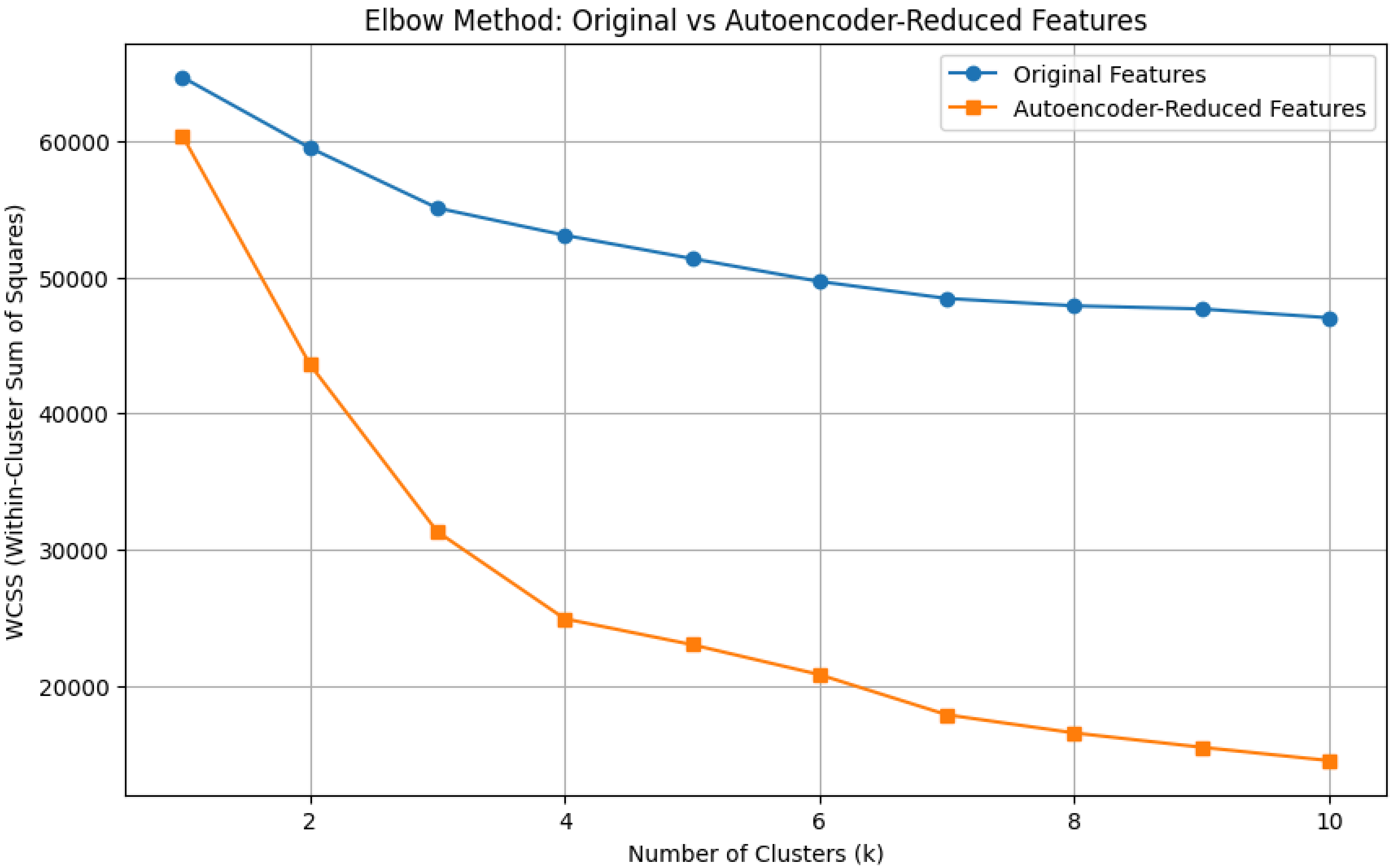
In [49]:

```
# Apply KMEANS to encoded dataset here
kmeans_encoded = KMeans(n_clusters=3, init='k-means++', random_state=42)
y_kmeans_encoded = kmeans_encoded.fit_predict(X_encoded)
```

In [50]:

```
# create a line plot to show the " Pick optimal number of clusters using Elbow method" of the unreduced and reduced dim
wcss_original = []
wcss_encoded = []

for k in range(1, 11):
    kmeans_orig = KMeans(n_clusters=k, init='k-means++', random_state=42)
    kmeans_orig.fit(X)
    wcss_original.append(kmeans_orig.inertia_)

    kmeans_enc = KMeans(n_clusters=k, init='k-means++', random_state=42)
    kmeans_enc.fit(X_encoded)
    wcss_encoded.append(kmeans_enc.inertia_)

plt.figure(figsize=(10, 6))

plt.plot(range(1, 11), wcss_original, marker='o', label='Original Features')
plt.plot(range(1, 11), wcss_encoded, marker='s', label='Autoencoder-Reduced Features')

plt.title('Elbow Method: Original vs Autoencoder-Reduced Features')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('WCSS (Within-Cluster Sum of Squares)')
plt.legend()
```

```
plt.grid(True)
plt.show()
```



In [51]:
```
## Apply the resulting optimal k to find new centroids
optimal_k = 3

kmeans_final = KMeans(n_clusters=optimal_k, init='k-means++', random_state=42)
kmeans_final.fit(X_encoded)

centroids = kmeans_final.cluster_centers_
```

In [52]:
```
## Show the centroids shape
print("Centroids shape:", kmeans_final.cluster_centers_.shape)
```

```
Centroids shape: (3, 8)
```

In [53]:
```
# show the clusters shape
print("Cluster assignments shape:", y_kmeans_encoded.shape)
```

```
Cluster assignments shape: (1470,)
```

In [54]:
```
# concatenate the clusters to the data
compressed_df = pd.DataFrame(X_encoded, columns=[f'Feature_{i}' for i in range(X_encoded.shape[1])])
compressed_df['Cluster'] = y_kmeans_encoded
compressed_df.head()
```

Out[54]:

	Feature_0	Feature_1	Feature_2	Feature_3	Feature_4	Feature_5	Feature_6	Feature_7	Cluster
0	1.568441	1.241364	0.593133	5.113352	2.302389	0.0	4.245976	7.492687	2
1	2.842677	0.955184	7.441913	2.292350	1.647639	0.0	5.434120	2.644839	0
2	1.698309	4.492142	8.864400	2.963076	6.616045	0.0	5.660383	4.766809	0
3	2.879568	4.075821	8.686769	5.247334	4.044940	0.0	8.881424	5.491131	0
4	1.023033	2.681492	6.395910	1.777609	4.102526	0.0	2.958478	3.924850	0

In [55]:
```
# show the 'Number of samples" in your current consolidated
print("Number of samples:", compressed_df.shape[0])
```

```
Number of samples: 1470
```

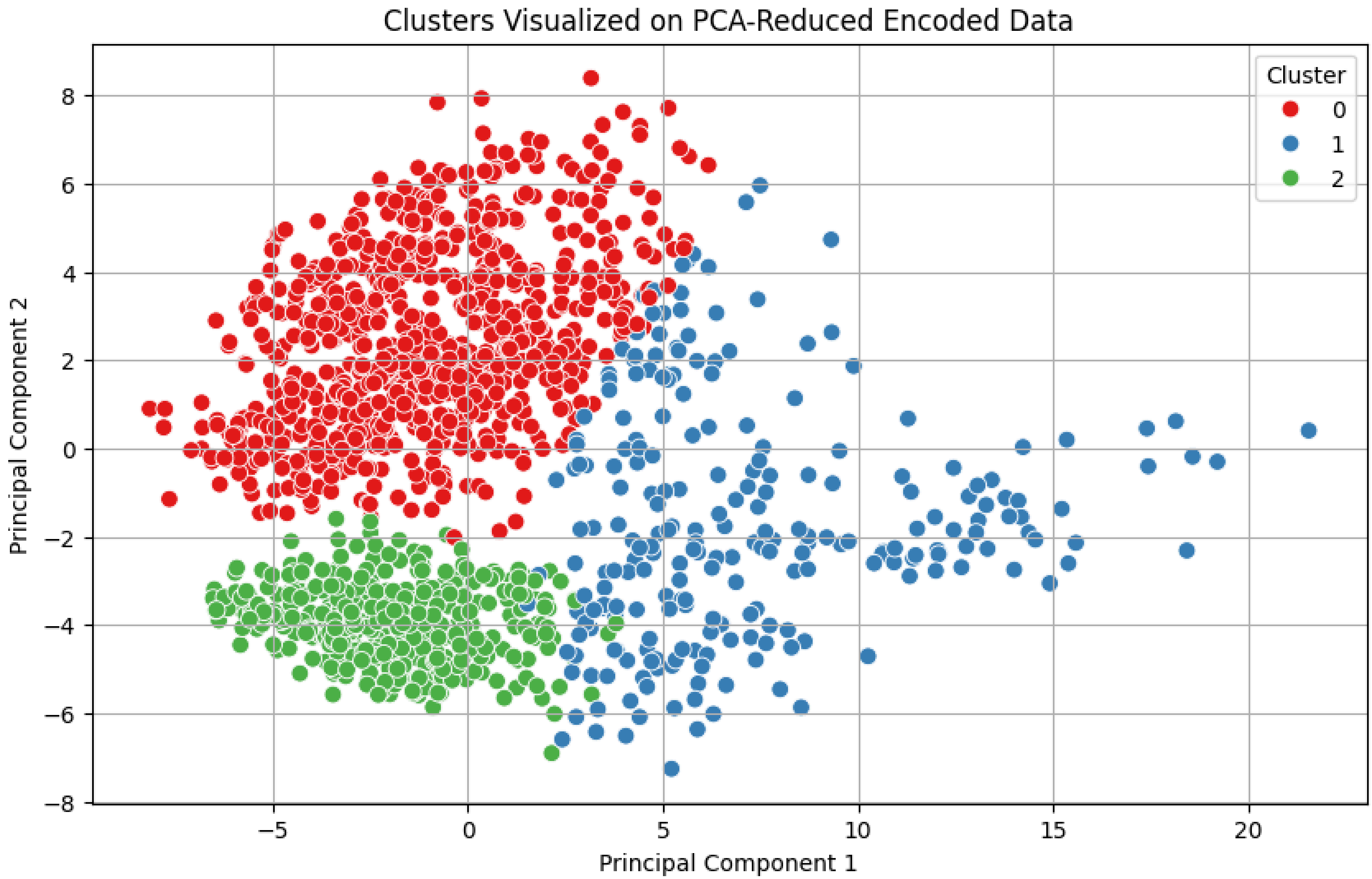
In [56]:
```
## Apply PCA to encoded dataset
pca_encoded = PCA(n_components=2)
X_pca_encoded = pca_encoded.fit_transform(X_encoded)
```

In [57]:
```
# concatenate the clusters to the data
pca_encoded_df = pd.DataFrame(X_pca_encoded, columns=['PC1', 'PC2'])
pca_encoded_df['Cluster'] = y_kmeans_encoded
```

In [58]:
```
## Apply PCA to encoded dataset
```

In [59]:
```
## Plot your pca scatterplot with clusters as the hue
plt.figure(figsize=(10, 6))

sns.scatterplot(data=pca_encoded_df, x='PC1', y='PC2', hue='Cluster', palette='Set1', s=60)
plt.title('Clusters Visualized on PCA-Reduced Encoded Data')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend(title='Cluster')
```

```
plt.grid(True)
plt.show()
```



In [ ]: