In [1]:
```
import csv
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report
from matplotlib.colors import ListedColormap
from sklearn import neighbors, datasets
```

```
/Users/shenstella/opt/anaconda3/lib/python3.9/site-packages/scipy/__init__.py:146: UserW
arning: A NumPy version >=1.16.5 and <1.23.0 is required for this version of SciPy (dete
cted version 1.26.0
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

Load the data

In [2]:
```
data = pd.read_csv('data.csv', parse_dates=['Intake-DateTime', 'Outcome-DateTime'])
data.dtypes
```

Out[2]:
```
AnimalID                          object
ID                                object
Breed                             object
Color                             object
Gender                            object
Name                              object
Intake-DateTime           datetime64[ns]
Intake-Type                       object
Intake-Condition                  object
Intake-Age(days)                   int64
Date-Of-Birth                     object
Outcome-DateTime          datetime64[ns]
Outcome-Type                      object
Outcome-Subtype                   object
Outcome-Age(days)                  int64
Age                               object
IsAdopted                           bool
Category                          object
Intelligence-Ranking               int64
Intelligence-Category             object
Size-Category                     object
Longevity                        float64
Total-Cost($)                      int64
Purchase-Cost($)                   int64
Food-Cost($)                       int64
Cost-Category                     object
dtype: object
```

In [3]:
```
data['ReFoundByShelter'] = data['ID'].str.contains('\+')
data
```

Out[3]:

	AnimalID	ID	Breed	Color	Gender	Name	Intake-DateTime	Intake-Type	Intake-Condition	Intake-Age(days)
0	A006100	A006100	Spinone Italiano	Yellow	Male	Scamp	2014-03-07 14:26:00	Public Assist	Normal	2190
1	A006100	A006100+	Spinone Italiano	Yellow	Male	Scamp	2014-12-19 10:21:00	Public Assist	Normal	2555
2	A006100	A006100++	Spinone Italiano	Yellow	Male	Scamp	2017-12-07 14:07:00	Stray	Normal	3650
3	A134067	A134067	Shetland Sheepdog	Brown	Male	Bandit	2013-11-16 09:02:00	Public Assist	Injured	12190
4	A141142	A141142	Labrador Retriever	Black	Female	Bettie	2013-11-16 14:46:00	Stray	Aged	11825
...	...	...	...	...	...	...	...	...	...	...
85791	A893431	A893431	Chihuahua	Tricolor	Female	Chili	2023-11-21 11:21:00	Public Assist	Normal	2920
85792	A893432	A893432	Chihuahua	Tan	Female	Coco	2023-11-21 11:21:00	Public Assist	Normal	2920
85793	A893452	A893452	Maltese	White	Female	Sophie	2023-11-21 13:38:00	Public Assist	Normal	2555
85794	A893529	A893529	Labrador Retriever	White	Female	Unknown	2023-11-22 14:26:00	Owner Surrender	Normal	30
85795	A893585	A893585	German Shepherd	Black	Male	Unknown	2023-11-23 20:19:00	Stray	Injured	30

85796 rows × 27 columns

In [4]:
```
y = data.iloc[:,26:27]
```

Prepare the data, replace object data with numerical values

In [5]:
```
X = data.iloc[:,:].drop(columns=["IsAdopted", "ReFoundByShelter", "AnimalID", "ID", "Int
X
```

Out[5]:

	Gender	Age	Intelligence-Ranking	Size-Category	Longevity	Total-Cost($)	Purchase-Cost($)	Food-Cost($)
0	Male	Adult	27	Large	9.00	18062	1725	5679
1	Male	Senior	27	Large	9.00	18062	1725	5679
2	Male	Senior	27	Large	9.00	18062	1725	5679
3	Male	Senior	6	Small	12.53	17469	465	3698
4	Female	Senior	7	Medium	12.04	18422	810	4819
...	...	...	...	...	...	...	...	...
85791	Female	Senior	67	Small	16.50	22640	588	4594
85792	Female	Senior	67	Small	16.50	22640	588	4594
85793	Female	Senior	59	Small	12.25	16073	650	2410
85794	Female	Baby	7	Medium	12.04	18422	810	4819
85795	Male	Baby	3	Large	9.73	15091	820	3895

85796 rows × 8 columns

In [6]:

```
# Here we replace all the descriptive lable into numerical lable
gender = X.groupby('Gender').size()
X['Gender'].replace(['Female','Male'], [0,1], inplace=True)
SizeCategory = X.groupby('Size-Category').size()
X['Size-Category'].replace(['Large','Medium','Small'], [3,2,1], inplace=True)
Age = X.groupby('Age').size()
X['Age'].replace(['Baby','Young','Adult', 'Senior'], [1,2,3,4], inplace=True)
X
```

Out[6]:

	Gender	Age	Intelligence-Ranking	Size-Category	Longevity	Total-Cost($)	Purchase-Cost($)	Food-Cost($)
0	1	3	27	3	9.00	18062	1725	5679
1	1	4	27	3	9.00	18062	1725	5679
2	1	4	27	3	9.00	18062	1725	5679
3	1	4	6	1	12.53	17469	465	3698
4	0	4	7	2	12.04	18422	810	4819
...	...	...	...	...	...	...	...	...
85791	0	4	67	1	16.50	22640	588	4594
85792	0	4	67	1	16.50	22640	588	4594
85793	0	4	59	1	12.25	16073	650	2410
85794	0	1	7	2	12.04	18422	810	4819
85795	1	1	3	3	9.73	15091	820	3895

85796 rows × 8 columns

In [7]:

```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
```

In [8]:

```
# kNN is sensitive to the scale of features, so it's a good idea to normalize the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [9]:
```python
# Choose the number of neighbors (you can experiment with different values)
n_neighbors = 3

# Create kNN classifier
knn = KNeighborsClassifier(n_neighbors=n_neighbors)

# Train the model
knn.fit(X_train_scaled, y_train.values.ravel())

# Make predictions
y_pred = knn.predict(X_test_scaled)
```

In [10]:
```python
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy}")
print("Classification Report:\n", report)
```

```
Accuracy: 0.8052447552447553
Classification Report:
               precision    recall  f1-score   support

       False       0.85      0.94      0.89     14543
        True       0.17      0.07      0.10      2617

    accuracy                           0.81     17160
   macro avg       0.51      0.50      0.50     17160
weighted avg       0.74      0.81      0.77     17160
```

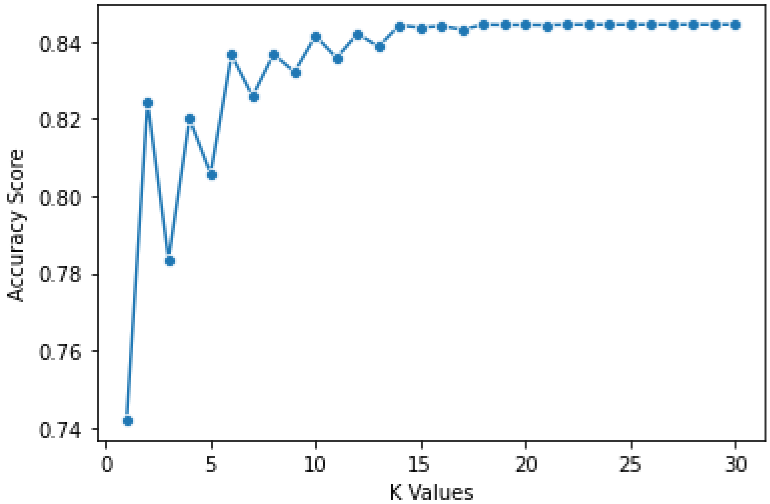
Using Cross Validation to Get the Best Value of k

In [11]:
```python
from sklearn.model_selection import cross_val_score
k_values = [i for i in range (1,31)]
scores = []

# Convert y_train to a NumPy array and then use ravel()
y_train_np = y_train.values.ravel()

X = scaler.fit_transform(X)

# Create kNN classifier
knn = KNeighborsClassifier(n_neighbors=n_neighbors)

# Train the model
knn.fit(X_train_scaled, y_train_np)
# Use cross_val_score
scores = []
for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    score = cross_val_score(knn, X_train_scaled, y_train_np, cv=5)
    scores.append(np.mean(score))
```

We can plot the results with the following code

In [12]:
```python
import seaborn as sns
sns.lineplot(x = k_values, y = scores, marker = 'o')
plt.xlabel("K Values")
plt.ylabel("Accuracy Score")
```

Out[12]: Text(0, 0.5, 'Accuracy Score')



Since we know know what could be the best K value, we update the model with the best K

In [14]:

```
best_index = np.argmax(scores)
best_k = k_values[best_index]

knn = KNeighborsClassifier(n_neighbors=best_k)
knn.fit(X_train_scaled, y_train_np)
```

Out[14]: KNeighborsClassifier(n_neighbors=26)

In [15]:

```
y_pred = knn.predict(X_test_scaled)

accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy}")
print("Classification Report:\n", report)
```

```
Accuracy: 0.8476689976689976
Classification Report:
               precision    recall  f1-score   support

       False       0.85      1.00      0.92     14543
        True       1.00      0.00      0.00      2617

    accuracy                           0.85     17160
   macro avg       0.92      0.50      0.46     17160
weighted avg       0.87      0.85      0.78     17160
```

evaluate with accuracy, precision, and recall

In [16]:

```
from sklearn.metrics import precision_score, recall_score

accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)

print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
```

```
Accuracy: 0.8476689976689976
Precision: 1.0
Recall: 0.0011463507833397019
```

In [17]:

```python
y_pred = knn.predict(X_test_scaled)
```

Use each feature alone - to fit a KNN model on the training set.

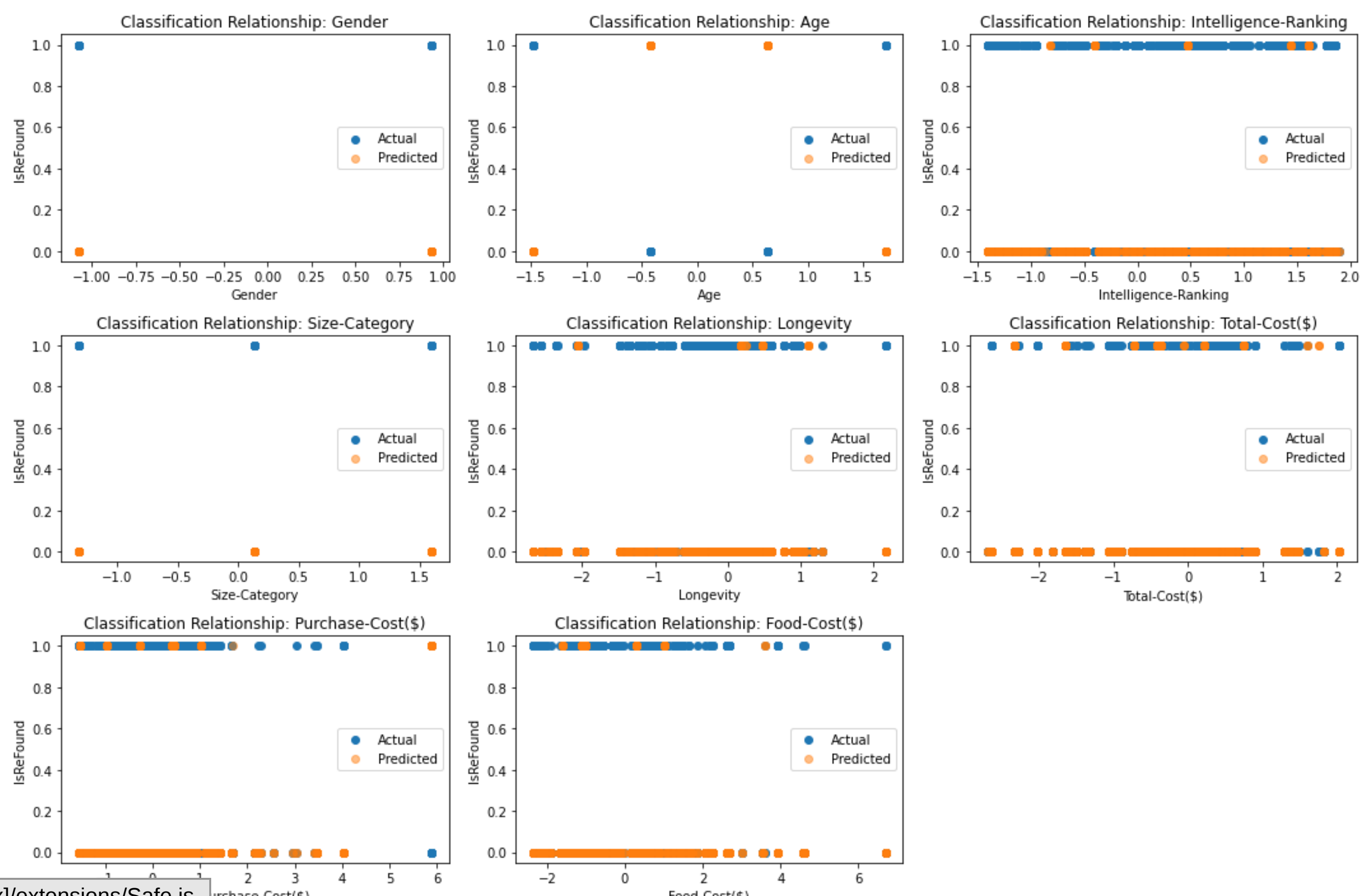
In [18]:

```python
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier

# Feature names
names = ["Gender", "Age", "Intelligence-Ranking", "Size-Category", "Longevity", "Total-C

plt.figure(figsize=(15, 10))

# Iterate over each feature
for i in range(len(names)):
    plt.subplot(3, 3, i + 1)

    # Extract the current feature
    x = X[:, i].reshape(-1, 1)

    # Split the data
    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_stat

    # Convert y_train to a NumPy array and then use ravel()
    y_train_np = y_train.values.ravel()

    # Create KNN classifier
    knn = KNeighborsClassifier(n_neighbors=3)

    # Train the model
    knn.fit(x_train, y_train_np)

    y_pred = knn.predict(x_test)

    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)

    print("Evaluation for the feature: ", names[i])
    print("Accuracy:", accuracy)
    print("Precision:", precision)
    print("Recall:", recall)

    # Visualize decision boundary
    plt.scatter(x_test, y_test, label='Actual')
    plt.scatter(x_test, knn.predict(x_test), label='Predicted', marker='o', alpha=0.5)

    plt.title(f"Classification Relationship: {names[i]}")
    plt.xlabel(names[i])
    plt.ylabel('IsReFound')
    plt.legend()

plt.tight_layout()
plt.show()
```

```
/Users/shenstella/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classificat
ion.py:1318: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due t
o no predicted samples. Use `zero_division` parameter to control this behavior.
verage, modifier, msg_start, len(result))
```

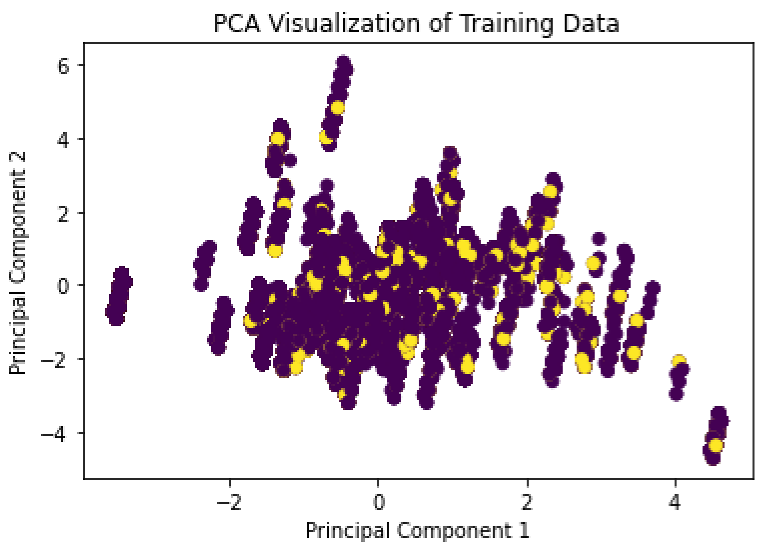
Loading [MathJax]/extensions/Safe.js

```
Evaluation for the feature:  Gender
Accuracy: 0.8474941724941725
Precision: 0.0
Recall: 0.0
Evaluation for the feature:  Age
Accuracy: 0.4244172494172494
Precision: 0.18489583333333334
Recall: 0.8139090561711884
Evaluation for the feature:  Intelligence-Ranking
Accuracy: 0.8251165501165502
Precision: 0.17235494880546076
Recall: 0.03859380970576996
/Users/shenstella/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
Evaluation for the feature:  Size-Category
Accuracy: 0.8474941724941725
Precision: 0.0
Recall: 0.0
Evaluation for the feature:  Longevity
Accuracy: 0.8374125874125874
Precision: 0.1685823754789272
Recall: 0.016813144822315627
Evaluation for the feature:  Total-Cost($)
Accuracy: 0.8136363636363636
Precision: 0.18526543878656554
Recall: 0.06534199465036301
Evaluation for the feature:  Purchase-Cost($)
Accuracy: 0.8057692307692308
Precision: 0.17395264116575593
Recall: 0.07298433320596102
Evaluation for the feature:  Food-Cost($)
Accuracy: 0.7314685314685314
Precision: 0.12448132780082988
Recall: 0.12609858616736722
```



Visualization

In [19]:
```
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA

# Apply PCA to reduce the data to 2 dimensions (you can adjust this based on the number
pca = PCA(n_components=2)
X_train_pca = pca.fit_transform(X_train_scaled)

# Plot the data points in 2D space with color-coded classes
plt.scatter(X_train_pca[:, 0], X_train_pca[:, 1], c=y_train_np, cmap='viridis')
plt.title('PCA Visualization of Training Data')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.show()
```



Conclusion & Discussion

From the Nearest Neighbor (kNN) Classifier model, we can see:

1. Age, Purchase cost, Food cost, Total-Cost do not affect if the pet will be refound by shelter.
2. Size, Gender, Longevity and Intelligence level have a high influence on whether this dog will be refound by shelter.
3. The model performs much better with all features rather than any individual ones. This quite makes sense since the model is better trained for classification.
4. The PCA plot suggests that to be refound by shelter is a complex decision that can't be easily predicted by one or two features alone.

In [ ]: