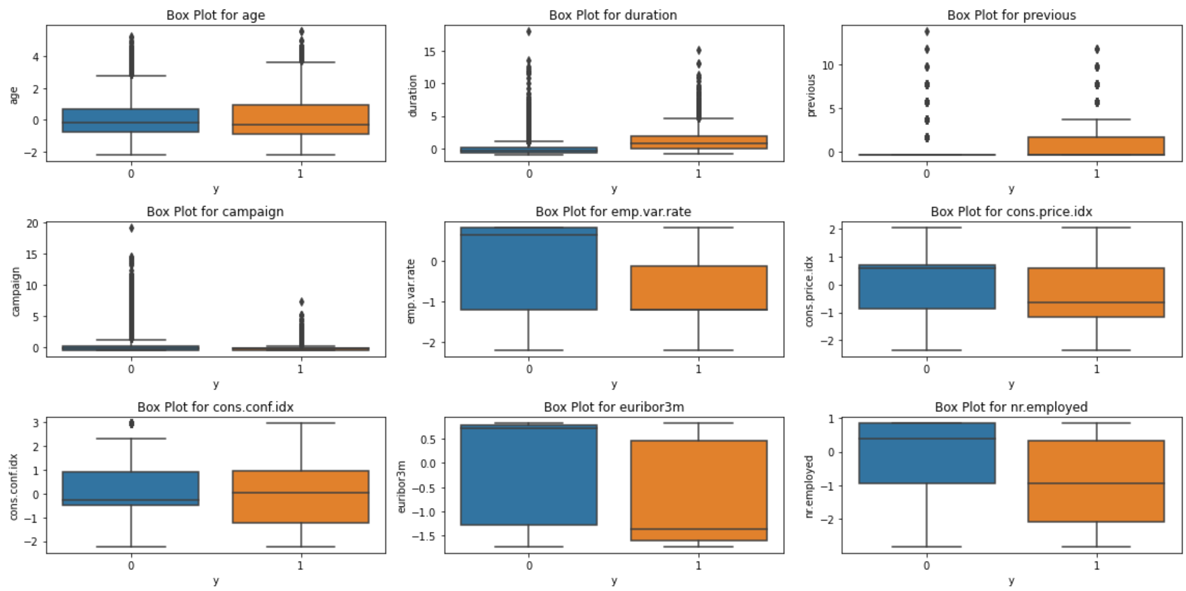
Anomaly Detection

In [47]:

```
import pandas as pd
from sklearn.cluster import DBSCAN
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import LocalOutlierFactor
from sklearn.cluster import KMeans

# Load the dataset
df = pd.read_csv('bank-additional-full.csv', sep=';')

# Preprocess the data
data = pd.get_dummies(df, columns=['job', 'marital', 'education', 'housing', 'month
data['y'] = df['y'].replace('no', '0')
data['y'] = data['y'].replace('yes', '1')
scaler = StandardScaler()
numerical_columns = ['age', 'duration', 'previous', 'campaign', 'emp.var.rate', 'co
                     'cons.conf.idx', 'euribor3m', 'nr.employed']
data[numerical_columns] = scaler.fit_transform(df[numerical_columns])
```

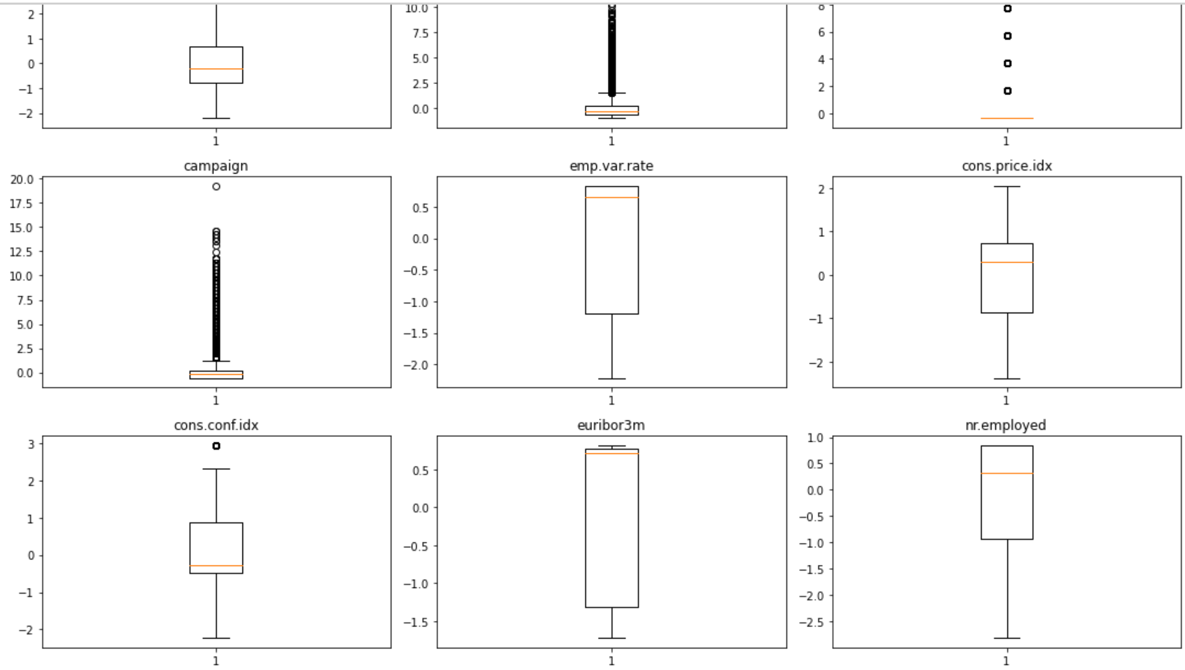
In [16]:

```
# Different Approaches for Anomaly Detection:

# 1- Box Plot for each variable
plt.figure(figsize=(16, 8))
for i, column in enumerate(numerical_columns, 1):
    plt.subplot(3, 3, i)
    sns.boxplot(x=data['y'], y=data[column])
    plt.title(f'Box Plot for {column}')
plt.tight_layout()
plt.show()
```



In [17]:

```
numerical columns for outlier detection
_columns = data[['age', 'duration', 'previous', 'campaign', 'emp.var.rate', 'cons.p

 for each variable
e(figsize=(15, 10))
l in enumerate(numerical_columns.columns, 1):
ubplot(3, 3, i)  # Use a 3x3 grid for the subplots
oxplot(numerical_columns[col])
itle(col)

_layout()
)
```



In [53]:

```
df[['age', 'duration', 'previous', 'campaign']].describe()
```

Out[53]:

	age	duration	previous	campaign
count	41188.00000	41188.000000	41188.000000	41188.000000
mean	40.02406	258.285010	0.172963	2.567593
std	10.42125	259.279249	0.494901	2.770014
min	17.00000	0.000000	0.000000	1.000000
25%	32.00000	102.000000	0.000000	1.000000
50%	38.00000	180.000000	0.000000	2.000000
75%	47.00000	319.000000	0.000000	3.000000
max	98.00000	4918.000000	7.000000	56.000000

With the plots and table above, I find that features such as age, balance, duration, campaign and previous all

In [28]:

```
#The average values of numerical variables for different Y values
print("The average values of numerical variables for different Y values: ")
df.pivot_table(['age', 'duration', 'previous', 'campaign'],['y'],aggfunc='mean')
```

```
The average values of numerical variables for different Y values:
```

Out[28]:

	age	campaign	duration	previous
y				
no	39.911185	2.633085	220.844807	0.132374
yes	40.913147	2.051724	553.191164	0.492672

In [14]:

```
# Select numerical columns for outlier detection
numerical_columns = data[['age', 'duration', 'previous', 'campaign', 'emp.var.rate'

# Calculate the first quartile (Q1) and third quartile (Q3)
Q1 = numerical_columns.quantile(0.25)
Q3 = numerical_columns.quantile(0.75)

# Calculate the Interquartile Range (IQR)
IQR = Q3 - Q1

# Define the lower and upper bounds for outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Identify outliers
outliers = ((numerical_columns < lower_bound) | (numerical_columns > upper_bound)).

# Display the number of outliers
print("Number of outliers:", outliers.sum())

# Display the indices of the outliers
print("Indices of outliers:", data.index[outliers])
```

```
Number of outliers: 10828
Indices of outliers: Int64Index([   37,    57,    61,    75,    83,
88,   111,   131,   164,
             169,
            ...
            41164, 41166, 41170, 41173, 41174, 41175, 41178, 41182, 4
1183,
            41187],
           dtype='int64', length=10828)
```

In [33]:

```
# Display all observations that have outliers
print("Observations with outliers:")
print(data[outliers])
```

```
Observations with outliers:
            age  default loan    contact  duration  campaign  pdays
previous  \
37     1.149199       no   no  telephone  5.429405 -0.565922    999 -
0.349494
57     0.477486  unknown   no  telephone  2.039197 -0.565922    999 -
0.349494
61     1.053240       no   no  telephone  2.135619 -0.565922    999 -
0.349494
75     0.093650  unknown   no  telephone  5.078428 -0.565922    999 -
0.349494
83     0.861322  unknown   no  telephone  3.022704 -0.565922    999 -
0.349494
...         ...      ...  ...        ...       ...       ...    ...
...
41175 -0.578062       no   no   cellular -0.301937 -0.565922    999
3.691766
41178  2.108788       no   no   cellular  0.866702 -0.204909      6
5.712397
41182 -1.057857       no   no   cellular -0.564206 -0.565922      9
1.671136
41183  3.164336       no   no   cellular  0.292025 -0.565922    999 -
0.349494
41187  3.260295       no   no   cellular -0.074380  0.156105    999
1.671136

          poutcome  emp.var.rate  ...  month_mar  month_may  month_no
v  \
37     nonexistent      0.648092  ...          0          1
0
57     nonexistent      0.648092  ...          0          1
0
61     nonexistent      0.648092  ...          0          1
0
75     nonexistent      0.648092  ...          0          1
0
83     nonexistent      0.648092  ...          0          1
0
...            ...           ...  ...        ...        ...
...
41175      failure     -0.752343  ...          0          0
1
41178      success     -0.752343  ...          0          0
1
41182      success     -0.752343  ...          0          0
1
41183  nonexistent     -0.752343  ...          0          0
1
41187      failure     -0.752343  ...          0          0
1

       month_oct month_sep  day_of_week_fri  day_of_week_mon  day_of_
week_thu  \
37             0         0                0                1
0
57             0         0                0                1
0
61             0         0                0                1
0
75             0         0                0                1
```

```
0
83              0         0                 0                1
0
...           ...       ...               ...              ...
...
41175           0         0                 0                0
1
41178           0         0                 0                0
1
41182           0         0                 1                0
0
41183           0         0                 1                0
0
41187           0         0                 1                0
0

       day_of_week_tue  day_of_week_wed
37                   0                0
57                   0                0
61                   0                0
75                   0                0
83                   0                0
...                ...              ...
41175                0                0
41178                0                0
41182                0                0
41183                0                0
41187                0                0

[10828 rows x 57 columns]
```

In [49]:

```python
# 2- Distance-based Approach: KNN Outlier Detection
features_distance = data[numerical_cols]
lof = LocalOutlierFactor(n_neighbors=5, contamination=0.1)
outlier_scores_distance = lof.fit_predict(features_distance)
outliers_distance = features_distance[outlier_scores_distance == -1]
print("Number of Distance-based outliers:", len(outliers_distance))
outlier_indices_distance = data.index[outlier_scores_distance == -1]
print("Indices of Distance-based outliers:", outlier_indices_distance)
```

```
Number of Distance-based outliers: 4119
Indices of Distance-based outliers: Int64Index([   12,    62,    80,
84,    97,   127,   139,   140,   158,
              162,
            ...
            41152, 41153, 41154, 41156, 41163, 41164, 41165, 41178, 4
1186,
            41187],
           dtype='int64', length=4119)
```

In [50]:

```
# 2- Distance-based Approach: KNN Outlier Detection
features_distance = data[numerical_cols]
lof = LocalOutlierFactor(n_neighbors=20, contamination=0.1)
outlier_scores_distance = lof.fit_predict(features_distance)
outliers_distance = features_distance[outlier_scores_distance == -1]
print("Number of Distance-based outliers:", len(outliers_distance))
outlier_indices_distance = data.index[outlier_scores_distance == -1]
print("Indices of Distance-based outliers:", outlier_indices_distance)
```

```
Number of Distance-based outliers: 4119
Indices of Distance-based outliers: Int64Index([    8,    26,    31,
84,   160,   163,   192,   228,   278,
              288,
            ...
            41157, 41160, 41161, 41164, 41166, 41174, 41177, 41184, 4
1186,
            41187],
           dtype='int64', length=4119)
```

In [51]:

```
# 2- Distance-based Approach: KNN Outlier Detection
features_distance = data[numerical_cols]
lof = LocalOutlierFactor(n_neighbors=100, contamination=0.1)
outlier_scores_distance = lof.fit_predict(features_distance)
outliers_distance = features_distance[outlier_scores_distance == -1]
print("Number of Distance-based outliers:", len(outliers_distance))
outlier_indices_distance = data.index[outlier_scores_distance == -1]
print("Indices of Distance-based outliers:", outlier_indices_distance)
```

```
Number of Distance-based outliers: 4119
Indices of Distance-based outliers: Int64Index([    9,    20,    84,
105,   110,   111,   192,   244,   288,
              355,
            ...
            41123, 41124, 41126, 41136, 41144, 41153, 41159, 41164, 4
1174,
            41183],
           dtype='int64', length=4119)
```

In [35]:

```
# Display all observations that have Distance-based outliers
print("Observations with Distance-based outliers:")
print(data.loc[outlier_indices_distance])
```

```
Observations with Distance-based outliers:
            age default loan    contact  duration  campaign  pdays  
previous  \
8     -1.537652      no   no  telephone  0.469442 -0.565922    999  -
0.349494
26     1.820911      no   no  telephone -0.637486 -0.565922    999  -
0.349494
31     1.820911      no   no  telephone  0.492583 -0.565922    999  -
0.349494
84    -0.194227      no  yes  telephone -0.919040 -0.565922    999  -
0.349494
160   -1.537652      no   no  telephone -0.359790 -0.204909    999  -
0.349494
...         ...     ...  ...        ...       ...       ...    ...   
...
41174  2.108788      no   no   cellular -0.193944 -0.565922      1  1
1.774288
41177  1.628993      no   no   cellular -0.517923  1.239145    999  -
0.349494
```

In [7]:

```
# 3- Density-based Approach: DBSCAN
features_density = data[numerical_cols]
dbscan = DBSCAN(eps=0.5, min_samples=5)
labels_density = dbscan.fit_predict(features_density)
outliers_density = features_density[labels_density == -1]
print("Number of Density-based outliers:", len(outliers_density))
```

```
Number of Density-based outliers: 2670
```

In [41]:

```
# Identify outliers based on DBSCAN labels
outliers_density_indices = data.index[labels_density == -1].tolist()
outliers_density = data.loc[outliers_density_indices]

print("Number of Density-based outliers:", len(outliers_density_indices))

# Display the indices of the Density-based outliers
print("Indices of Density-based outliers:", outliers_density_indices)

# Display all observations that have Density-based outliers
if not outliers_density.empty:
    print("Observations with Density-based outliers:")
    print(outliers_density)
else:
    print("No observations with Density-based outliers.")
```

```
Number of Density-based outliers: 2670
Indices of Density-based outliers: [37, 164, 590, 943, 1114, 1396, 16
89, 1791, 1809, 1839, 1853, 1980, 2031, 2105, 2313, 2330, 2610, 2970,
3127, 3219, 3370, 3413, 3418, 3427, 3438, 3484, 3514, 3532, 3539, 365
2, 3671, 3770, 3772, 3773, 3774, 3785, 3809, 3817, 3854, 3868, 3872,
3892, 4039, 4045, 4056, 4107, 4114, 4139, 4140, 4152, 4164, 4168, 417
6, 4213, 4221, 4264, 4353, 4410, 4456, 4575, 4650, 4847, 4880, 4897,
4902, 4942, 4978, 5017, 5043, 5073, 5112, 5304, 5337, 5384, 5386, 541
5, 5476, 5530, 5550, 5564, 5699, 5784, 5791, 5894, 5948, 6100, 6203,
6280, 6365, 6394, 6531, 6534, 6619, 6738, 6778, 6860, 7155, 7251, 727
7, 7297, 7302, 7390, 7542, 7544, 7613, 7629, 7700, 7714, 7719, 7727,
7753, 7841, 7945, 8014, 8016, 8097, 8099, 8101, 8102, 8125, 8130, 822
2, 8233, 8246, 8301, 8339, 8346, 8362, 8379, 8417, 8435, 8437, 8455,
8471, 8489, 8528, 8529, 8617, 8637, 8640, 8643, 8661, 8712, 8740, 876
5, 8952, 9013, 9048, 9057, 9072, 9095, 9149, 9160, 9196, 9205, 9251,
9258, 9276, 9346, 9432, 9487, 9524, 9759, 9785, 9811, 9937, 9951, 996
9, 9974, 9987, 9988, 9991, 9999, 10016, 10025, 10037, 10061, 10114, 1
0124, 10157, 10158, 10160, 10162, 10184, 10224, 10233, 10239, 10254,
10299, 10310, 10337, 10354, 10431, 10455, 10456, 10466, 10478, 10488,
```

In [ ]: