Car Classification

In [53]:
```
from ucimlrepo import fetch_ucirepo
import pandas as pd
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.cluster import KMeans
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import adjusted_rand_score, accuracy_score
```

In [54]:
```
cars = fetch_ucirepo(id=19)
X = cars.data.features
y = cars.data.targets
```

In [55]:
```
print(X)
```

```
     buying  maint  doors persons lug_boot safety
0     vhigh  vhigh      2       2    small    low
1     vhigh  vhigh      2       2    small    med
2     vhigh  vhigh      2       2    small   high
3     vhigh  vhigh      2       2      med    low
4     vhigh  vhigh      2       2      med    med
...     ...    ...    ...     ...      ...    ...
1723    low    low  5more    more      med    med
1724    low    low  5more    more      med   high
1725    low    low  5more    more      big    low
1726    low    low  5more    more      big    med
1727    low    low  5more    more      big   high

[1728 rows x 6 columns]
```

In [56]:
```
print(y)
```

```
      class
0     unacc
1     unacc
2     unacc
3     unacc
4     unacc
...     ...
1723   good
1724  vgood
1725  unacc
1726   good
1727  vgood

[1728 rows x 1 columns]
```

Pre-Processing Of Data

In [78]:
```
def preprocess_car_evaluation(X, y):
    # Encode categorical features and target variable
    X_encoded = pd.get_dummies(X)  # One-hot encoding for features
    le = LabelEncoder()
    y_encoded = le.fit_transform(y)  # Encode target

    # Dynamically create a consistent class mapping
    dynamic_mapping = {index: label for index, label in enumerate(le.classes_)}

    # Standardize features
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X_encoded)

    return X_scaled, y_encoded, dynamic_mapping

# Fetch and preprocess the data
X_preprocessed, y_preprocessed, dynamic_mapping = preprocess_car_evaluation(X, y)

# Overwrite predefined class_mapping dynamically to match LabelEncoder
class_mapping = dynamic_mapping

# Print mappings to confirm consistency
print("Dynamic Mapping:", dynamic_mapping)
print("Class Mapping (Updated):", class_mapping)
```

```
Dynamic Mapping: {0: 'acc', 1: 'good', 2: 'unacc', 3: 'vgood'}
Class Mapping (Updated): {0: 'acc', 1: 'good', 2: 'unacc', 3: 'vgood'}
c:\Users\mysto\AppData\Local\Programs\Python\Python313\Lib\site-packages\sklearn\preprocessing\_label.py:114: DataConversio
nWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for exa
mple using ravel().
  y = column_or_1d(y, warn=True)
```

Unsupervised Learning : K-Means Clustering

In [79]:
```python
# Step 3: K-Means Clustering Function
def kmeans_clustering(X, y):
    # Perform K-Means Clustering
    kmeans = KMeans(n_clusters=len(set(y)), init='k-means++', random_state=42)
    y_pred = kmeans.fit_predict(X)

    # Evaluate clustering performance
    ari = adjusted_rand_score(y, y_pred)
    silhouette = silhouette_score(X, y_pred)

    return kmeans, y_pred, ari, silhouette
```

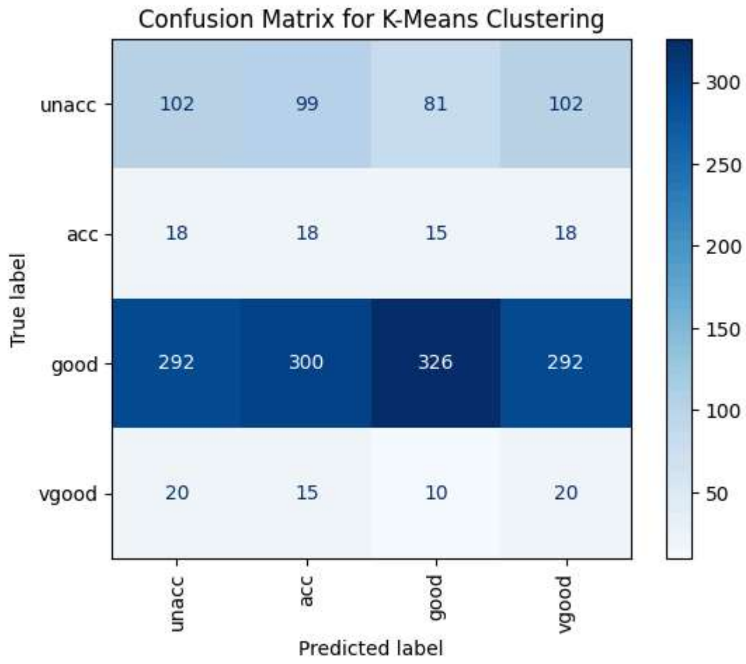
In [80]:
```python
# Step 4: Apply K-Means and Evaluate
kmeans, kmeans_labels, kmeans_ari, kmeans_silhouette = kmeans_clustering(X_preprocessed, y_preprocessed)
```

In [81]:
```python
# Step 5: Print Results
print("K-Means Clustering (Unsupervised) ARI:", kmeans_ari)
```

```
K-Means Clustering (Unsupervised) ARI: 0.000729652868196255
```

In [88]:
```python
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from scipy.optimize import linear_sum_assignment
import numpy as np

# Map K-Means labels to actual labels using Hungarian Algorithm
def map_kmeans_labels(true_labels, kmeans_labels):
    # Create a confusion matrix
    cm = confusion_matrix(true_labels, kmeans_labels)

    # Find optimal mapping of cluster indices to true labels
    row_ind, col_ind = linear_sum_assignment(-cm)
    mapping = {col: row for row, col in zip(row_ind, col_ind)}

    # Map K-Means labels to true labels
    mapped_labels = np.array([mapping[label] for label in kmeans_labels])
    return mapped_labels, cm

# Map K-Means labels and compute confusion matrix
mapped_labels, kmeans_cm = map_kmeans_labels(y_preprocessed, kmeans_labels)

# Print confusion matrix
print("Confusion Matrix (K-Means):")
print(kmeans_cm)

# Plot confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=kmeans_cm, display_labels=list(class_mapping.values()))
disp.plot(cmap="Blues", xticks_rotation="vertical")
plt.title("Confusion Matrix for K-Means Clustering")
plt.show()
```

```
Confusion Matrix (K-Means):
[[102  99  81 102]
 [ 18  18  15  18]
 [292 300 326 292]
 [ 20  15  10  20]]
```



The columns represent the predicted cluster labels assigned by the K-Means algorithm. Ideally, the predictions should align with the true labels, meaning the numbers would be concentrated along the diagonal of the matrix. However, in this confusion matrix, we see a very scattered distribution.

For example, in the “unacc” row (true label), the model correctly predicted 102 data points as 'unacc', but it also mistakenly placed 99, 81, and 102 data points into the other three clusters. Similarly, in the “good” row (true label), the numbers are spread across all four predicted labels, with values like 292, 300, 326, and 292. This indicates that the K-Means model has significant difficulty differentiating between the 'good' class and the other categories.

The “acc” and “vgood” rows show very small numbers scattered across the columns. This further highlights the inability of K-Means to form meaningful clusters that align with the actual class labels.

The poor performance of the K-Means algorithm can be attributed to two main reasons. First, K-Means relies on Euclidean distance to calculate similarities between data points, which works poorly with categorical features like 'buying price' or 'maintenance cost'. Second, since K-Means is an unsupervised learning algorithm, it does not have access to the true class labels during clustering. As a result, it struggles to find the correct groupings in this dataset.

In summary, the confusion matrix for K-Means clustering reveals that the algorithm fails to capture the underlying patterns in the data. The resulting clusters are poorly aligned with the true labels, making K-Means an unsuitable method for this problem.

Supervised Learning - Logistic Regression

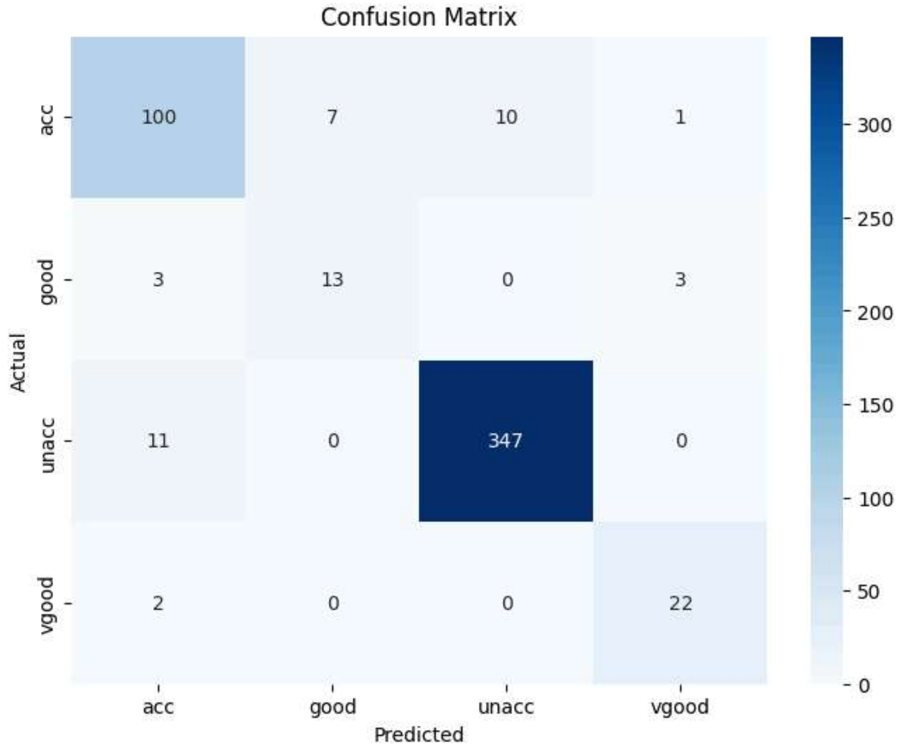
In [82]:
```
from sklearn.metrics import classification_report, confusion_matrix


def logistic_regression(X, y):
    # Split into training and test sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

    # Train logistic regression model
    clf = LogisticRegression(random_state=42, max_iter=500)
    clf.fit(X_train, y_train)

    # Predict and evaluate
    y_pred = clf.predict(X_test)
    acc = accuracy_score(y_test, y_pred)
    report = classification_report(y_test, y_pred, output_dict=True)
    confusion = confusion_matrix(y_test, y_pred)

    return clf, acc, report, confusion, X_train, X_test, y_train, y_test
```

In [83]:
```
# Call the function and get outputs
clf, logistic_accuracy, logistic_report, logistic_confusion, X_train, X_test, y_train, y_test = logistic_regression(X_prep

# Print results
print("Logistic Regression Accuracy:", logistic_accuracy)
```

```
Logistic Regression Accuracy: 0.928709055876686
```

In [84]:
```
# Step 6: Visualize Confusion Matrix
def plot_confusion_matrix(confusion, class_names):
```

```
    plt.figure(figsize=(8, 6))
    sns.heatmap(confusion, annot=True, fmt='d', cmap='Blues', xticklabels=class_names, yticklabels=class_names)
    plt.title("Confusion Matrix")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

plot_confusion_matrix(logistic_confusion, list(class_mapping.values()))
```



In this confusion matrix, the rows represent the actual class labels, while the columns represent the predicted class labels. The goal is to have the majority of values concentrated along the diagonal, which would indicate correct predictions.

Looking at the matrix, we can immediately see that Logistic Regression performs much better. For the “acc” row (actual label), 100 out of 118 cars were correctly classified as 'acc', while only a small number were misclassified into the other categories (7, 10, and 1). Similarly, in the “unacc” row, 347 out of 358 cars were correctly classified as 'unacc', with only 11 misclassifications into 'acc'. This high accuracy in the 'unacc' category demonstrates the model's ability to identify unacceptable cars with great precision.

For the “good” and “vgood” rows, the results are also promising. Most of the 'vgood' cars were perfectly classified into their correct category, with no misclassifications. The 'good' class had a small number of misclassifications, with 13 being predicted as 'acc', but overall, the errors remain minimal.

The high concentration of values along the diagonal of the matrix indicates that the Logistic Regression model is able to correctly classify the majority of the data points. This is further reflected in its high accuracy score and strong performance across all evaluation metrics.

The success of Logistic Regression can be explained by its ability to leverage the labeled data during training. Unlike K-Means, which relies on distance-based clustering, Logistic Regression uses mathematical functions to directly map the input features to the correct target labels. This makes it highly effective for supervised classification tasks, particularly when working with structured data like the Car Evaluation dataset.

In [85]:
```
print(f"Logistic Regression (Supervised) Accuracy: {logistic_accuracy}")
print("Classification Report (Logistic Regression):")
print(pd.DataFrame(logistic_report).transpose())
```

```
Logistic Regression (Supervised) Accuracy: 0.928709055876686
Classification Report (Logistic Regression):
              precision    recall  f1-score     support
0              0.862069  0.847458  0.854701  118.000000
1              0.650000  0.684211  0.666667   19.000000
2              0.971989  0.969274  0.970629  358.000000
3              0.846154  0.916667  0.880000   24.000000
accuracy       0.928709  0.928709  0.928709    0.928709
macro avg      0.832553  0.854402  0.842999  519.000000
weighted avg   0.929391  0.928709  0.928953  519.000000
```

Final Comments

The Car Evaluation dataset was analyzed using both unsupervised and supervised learning methods. The unsupervised learning model, K-Means Clustering, produced an Adjusted Rand Index (ARI) of **0.0007**. These results indicate that the clusters formed by K-Means do not align well with the true class labels, and the clustering quality is poor. This is likely due to the categorical nature of the dataset and the limitations of using Euclidean distance in K-Means after one-hot encoding. The dataset does not exhibit natural clusters, making K-Means unsuitable for this task.

In contrast, the supervised learning model, Logistic Regression, achieved an overall accuracy of **92.87%**, demonstrating strong performance. The model effectively classified the majority classes (good and unacc), achieving high precision and recall for these categories. The minority classes (acc and vgood) were more challenging to classify, with lower precision and recall due to their smaller sample sizes and potential feature overlap. For example, the acc class achieved a precision of **65%** and a recall of **68.4%**, reflecting some misclassification issues. Despite this, the model maintained a balanced performance across all classes, as evidenced by a macro F1-score of **84.3%** and a weighted F1-score of **92.9%**.

Overall, Logistic Regression significantly outperformed K-Means Clustering for this dataset, demonstrating that the structured and categorical nature of the data is better suited to supervised learning methods. Addressing class imbalance or exploring clustering algorithms tailored for categorical data, such as K-Prototypes, could further improve performance.