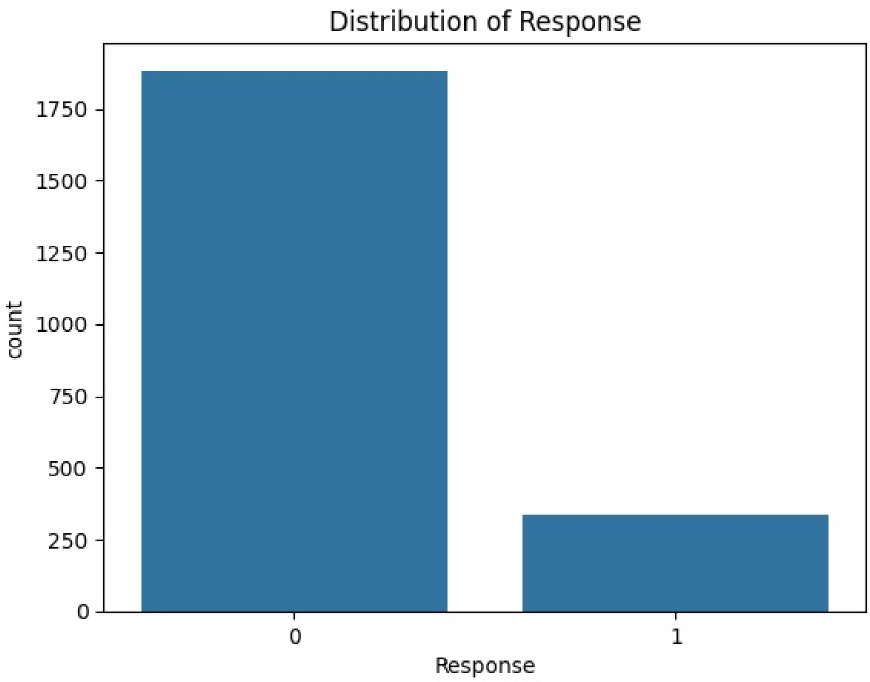
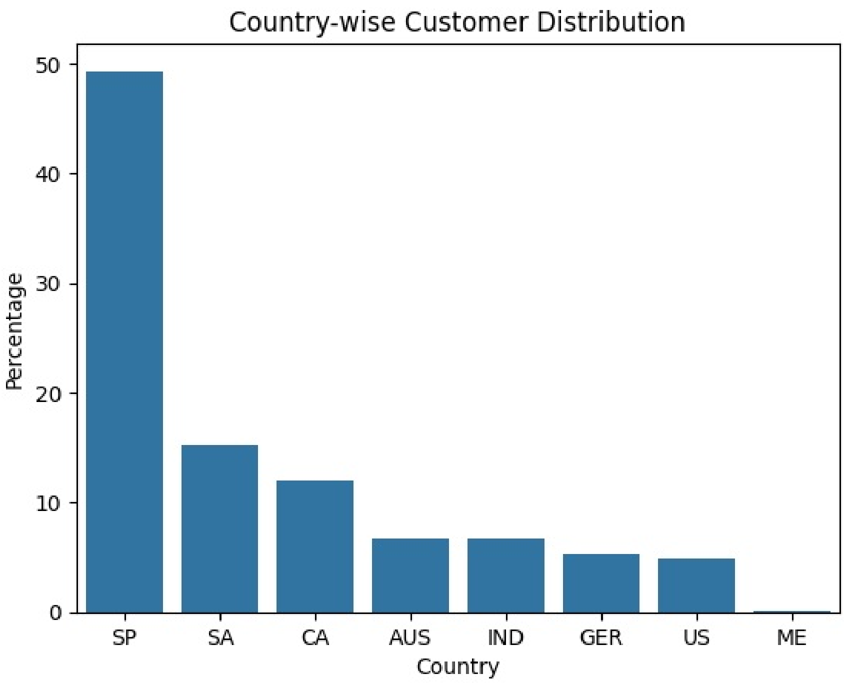
In [1]:
```python
# Step 1: Import necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report, roc_auc_score, RocCurveDisplay

# Step 2: Load the dataset
df = pd.read_csv('marketing_campaign.csv')

# Step 3: Display a sample of five rows
print(df.head())

# Step 4: Check the shape of the dataset
print(f"Dataset shape: {df.shape}")

# Step 5: Get general information about the dataset
print(df.info())

# Step 6: Check for missing values
missing_percent = df.isnull().sum() / len(df) * 100
print("Percentage of Missing Values:")
print(missing_percent[missing_percent > 0])

# Drop missing values if necessary
df = df.dropna()

# Step 7: Check for duplicate rows
print(f"Number of duplicate rows: {df.duplicated().sum()}")

# Step 8: Clean column names (e.g., remove extra spaces)
df.rename(columns=lambda x: x.strip(), inplace=True)

# Step 9: Convert 'Income' to numeric
df['Income'] = df['Income'].str.replace('[\$\,]', '', regex=True).astype(float)

# Step 10: Get basic statistics of the data
print(df.describe())
```

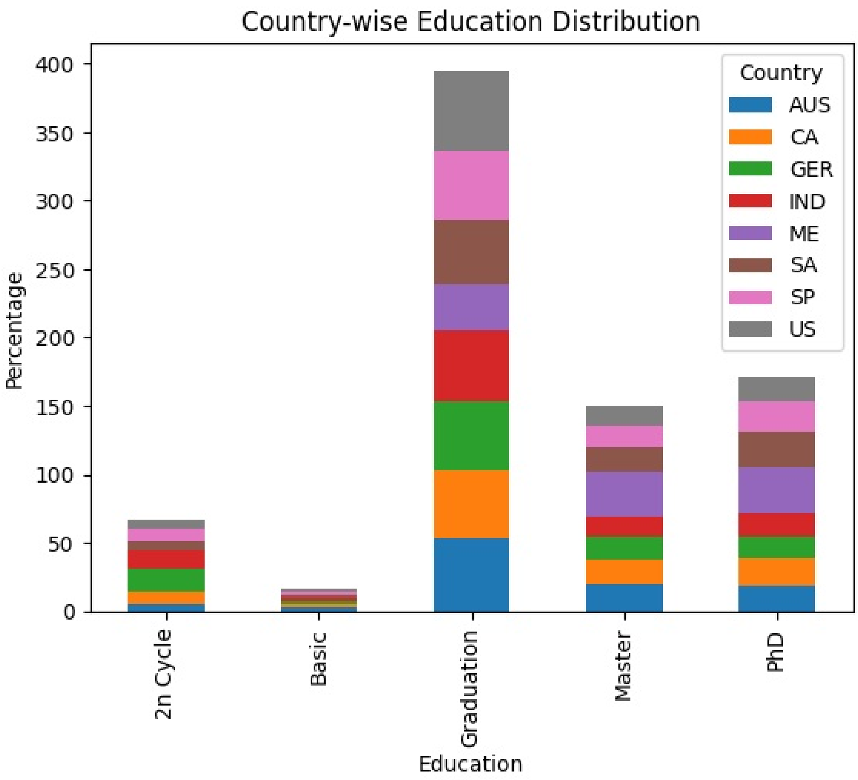
```
      ID  Year_Birth   Education Marital_Status      Income  Kidhome  \
0   1826        1970  Graduation       Divorced  $84,835.00        0
1      1        1961  Graduation         Single  $57,091.00        0
2  10476        1958  Graduation        Married  $67,267.00        0
3   1386        1967  Graduation       Together  $32,474.00        1
4   5371        1989  Graduation         Single  $21,474.00        1

   Teenhome Dt_Customer  Recency  MntWines  ...  NumStorePurchases  \
0         0     6-16-14        0       189  ...                  6
1         0     6-15-14        0       464  ...                  7
2         1     5-13-14        0       134  ...                  5
3         1     5-11-14        0        10  ...                  2
4         0      4-8-14        0         6  ...                  2

   NumWebVisitsMonth  AcceptedCmp3  AcceptedCmp4  AcceptedCmp5  AcceptedCmp1  \
0                  1             0             0             0             0
1                  5             0             0             0             0
2                  2             0             0             0             0
3                  7             0             0             0             0
4                  7             1             0             0             0

   AcceptedCmp2  Response  Complain  Country
0             0         1         0       SP
1             1         1         0       CA
2             0         0         0       US
3             0         0         0      AUS
4             0         1         0       SP

[5 rows x 28 columns]
Dataset shape: (2240, 28)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 28 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   ID                   2240 non-null   int64
 1   Year_Birth           2240 non-null   int64
 2   Education            2240 non-null   object
```

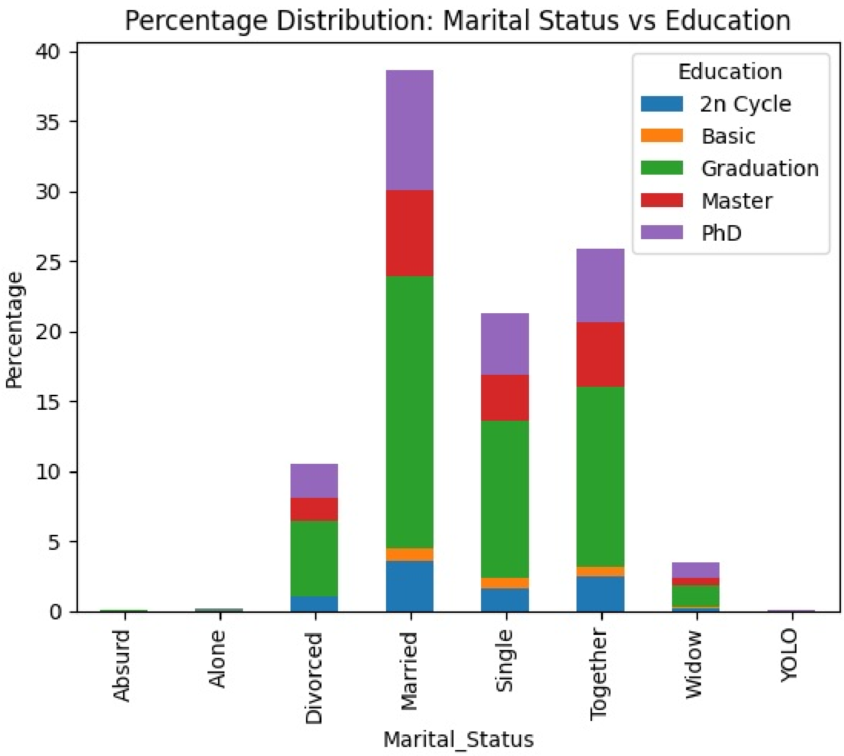
```
 3   Marital_Status       2240 non-null   object
 4   Income               2216 non-null   object
 5   Kidhome              2240 non-null   int64
 6   Teenhome             2240 non-null   int64
 7   Dt_Customer          2240 non-null   object
 8   Recency              2240 non-null   int64
 9   MntWines             2240 non-null   int64
 10  MntFruits            2240 non-null   int64
 11  MntMeatProducts      2240 non-null   int64
 12  MntFishProducts      2240 non-null   int64
 13  MntSweetProducts     2240 non-null   int64
 14  MntGoldProds         2240 non-null   int64
 15  NumDealsPurchases    2240 non-null   int64
 16  NumWebPurchases      2240 non-null   int64
 17  NumCatalogPurchases  2240 non-null   int64
 18  NumStorePurchases    2240 non-null   int64
 19  NumWebVisitsMonth    2240 non-null   int64
 20  AcceptedCmp3         2240 non-null   int64
 21  AcceptedCmp4         2240 non-null   int64
 22  AcceptedCmp5         2240 non-null   int64
 23  AcceptedCmp1         2240 non-null   int64
 24  AcceptedCmp2         2240 non-null   int64
 25  Response             2240 non-null   int64
 26  Complain             2240 non-null   int64
 27  Country              2240 non-null   object
dtypes: int64(23), object(5)
memory usage: 490.1+ KB
None
Percentage of Missing Values:
Income    1.071429
dtype: float64
Number of duplicate rows: 0
                 ID   Year_Birth         Income      Kidhome     Teenhome  \
count   2216.000000  2216.000000    2216.000000  2216.000000  2216.000000
mean    5588.353339  1968.820397   52247.251354     0.441787     0.505415
std     3249.376275    11.985554   25173.076661     0.536896     0.544181
min        0.000000  1893.000000    1730.000000     0.000000     0.000000
25%     2814.750000  1959.000000   35303.000000     0.000000     0.000000
50%     5458.500000  1970.000000   51381.500000     0.000000     0.000000
75%     8421.750000  1977.000000   68522.000000     1.000000     1.000000
max    11191.000000  1996.000000  666666.000000     2.000000     2.000000

           Recency     MntWines    MntFruits  MntMeatProducts  \
count  2216.000000  2216.000000  2216.000000      2216.000000
mean     49.012635   305.091606    26.356047       166.995939
std      28.948352   337.327920    39.793917       224.283273
min       0.000000     0.000000     0.000000         0.000000
25%      24.000000    24.000000     2.000000        16.000000
50%      49.000000   174.500000     8.000000        68.000000
75%      74.000000   505.000000    33.000000       232.250000
max      99.000000  1493.000000   199.000000      1725.000000

       MntFishProducts  ...  NumCatalogPurchases  NumStorePurchases  \
count      2216.000000  ...          2216.000000        2216.000000
mean         37.637635  ...             2.671029           5.800993
std          54.752082  ...             2.926734           3.250785
min           0.000000  ...             0.000000           0.000000
25%           3.000000  ...             0.000000           3.000000
50%          12.000000  ...             2.000000           5.000000
75%          50.000000  ...             4.000000           8.000000
max         259.000000  ...            28.000000          13.000000

       NumWebVisitsMonth  AcceptedCmp3  AcceptedCmp4  AcceptedCmp5  \
count        2216.000000   2216.000000   2216.000000   2216.000000
mean            5.319043      0.073556      0.074007      0.073105
std             2.425359      0.261106      0.261842      0.260367
min             0.000000      0.000000      0.000000      0.000000
25%             3.000000      0.000000      0.000000      0.000000
50%             6.000000      0.000000      0.000000      0.000000
75%             7.000000      0.000000      0.000000      0.000000
max            20.000000      1.000000      1.000000      1.000000

       AcceptedCmp1  AcceptedCmp2     Response     Complain
count   2216.000000   2216.000000  2216.000000  2216.000000
mean       0.064079      0.013538     0.150271     0.009477
std        0.244950      0.115588     0.357417     0.096907
min        0.000000      0.000000     0.000000     0.000000
25%        0.000000      0.000000     0.000000     0.000000
50%        0.000000      0.000000     0.000000     0.000000
75%        0.000000      0.000000     0.000000     0.000000
max        1.000000      1.000000     1.000000     1.000000

[8 rows x 24 columns]
```

In [2]:
```python
# Step 1: Distribution of the target variable
sns.countplot(x='Response', data=df)
plt.title('Distribution of Response')
plt.show()

# Step 2: Percentage distribution of customers by country
country_dist = df['Country'].value_counts(normalize=True) * 100
sns.barplot(x=country_dist.index, y=country_dist.values)
plt.title('Country-wise Customer Distribution')
plt.ylabel('Percentage')
plt.show()

# Step 3: Qualification distribution country-wise
qualification_country = pd.crosstab(df['Education'], df['Country'], normalize='columns') * 100
qualification_country.plot(kind='bar', stacked=True)
plt.title('Country-wise Education Distribution')
plt.ylabel('Percentage')
plt.show()

# Step 4: Marital Status and Education Percentage Segment
marital_education = pd.crosstab(df['Marital_Status'], df['Education'], normalize=True) * 100
marital_education.plot(kind='bar', stacked=True)
plt.title('Percentage Distribution: Marital Status vs Education')
plt.ylabel('Percentage')
plt.show()
```







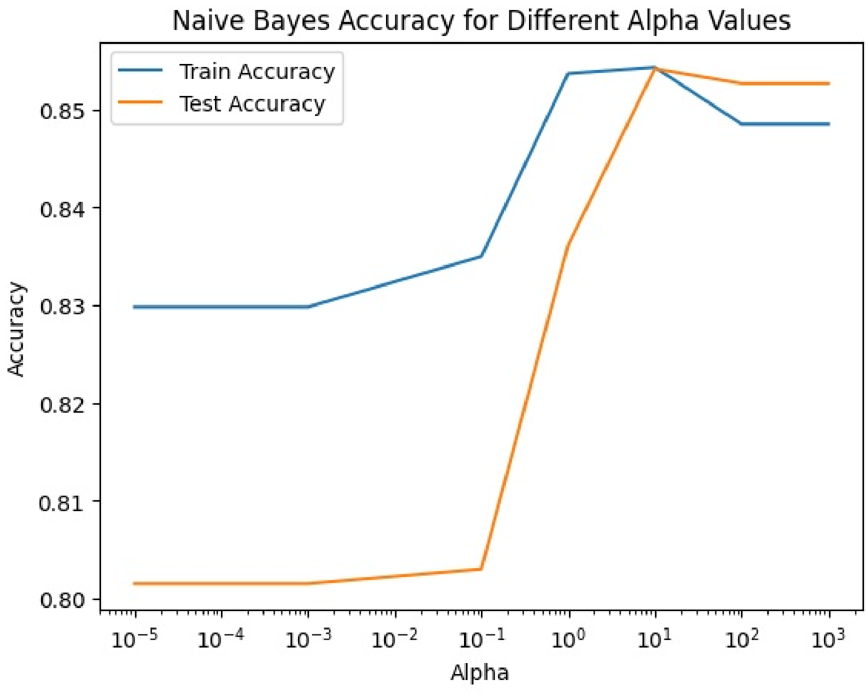


In [3]:
```
# Step 1: Drop unwanted columns
columns_to_drop = ['ID', 'Year_Birth', 'Dt_Customer', 'Country', 'Education', 'Marital_Status']
df = df.drop(columns=columns_to_drop)

# Step 2: Encode categorical variables
le = LabelEncoder()
categorical_cols = df.select_dtypes(include='object').columns
for col in categorical_cols:
    df[col] = le.fit_transform(df[col])

# Step 3: Split features and target
X = df.drop('Response', axis=1)
y = df['Response']

# Step 4: Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Step 5: Standardize numerical features
```

```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [4]:

```
# Step 1: Train Naive Bayes with various alpha values
alpha_values = [0.00001, 0.0001, 0.001, 0.1, 1, 10, 100, 1000]
train_accuracies = []
test_accuracies = []

for alpha in alpha_values:
    model = GaussianNB(var_smoothing=alpha)
    model.fit(X_train, y_train)
    train_accuracies.append(accuracy_score(y_train, model.predict(X_train)))
    test_accuracies.append(accuracy_score(y_test, model.predict(X_test)))

# Step 2: Plot error rates
plt.plot(alpha_values, train_accuracies, label='Train Accuracy')
plt.plot(alpha_values, test_accuracies, label='Test Accuracy')
plt.xscale('log')
plt.xlabel('Alpha')
plt.ylabel('Accuracy')
plt.legend()
plt.title('Naive Bayes Accuracy for Different Alpha Values')
plt.show()

# Step 3: Evaluate the best model
best_alpha = alpha_values[np.argmax(test_accuracies)]
model = GaussianNB(var_smoothing=best_alpha)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

print(f"Best Alpha: {best_alpha}")
print(f"Accuracy: {accuracy_score(y_test, y_pred)}")
print(classification_report(y_test, y_pred))
```

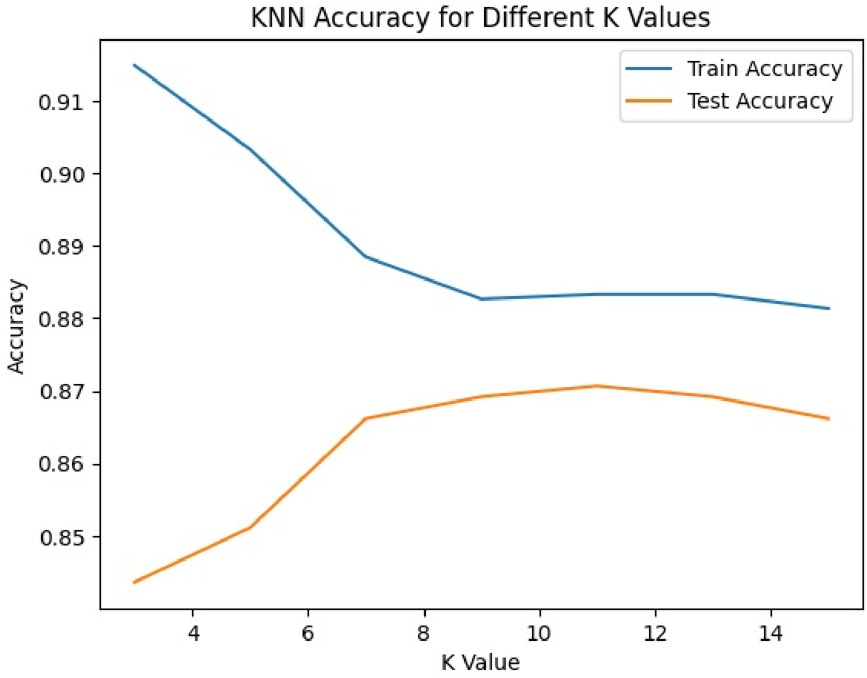



```
Best Alpha: 10
Accuracy: 0.8541353383458646
              precision    recall  f1-score   support

           0       0.85      1.00      0.92       567
           1       1.00      0.01      0.02        98

    accuracy                           0.85       665
   macro avg       0.93      0.51      0.47       665
weighted avg       0.88      0.85      0.79       665
```

In [5]:

```
# Step 1: Train KNN with various k values
k_values = [3, 5, 7, 9, 11, 13, 15]
train_accuracies = []
test_accuracies = []

for k in k_values:
    model = KNeighborsClassifier(n_neighbors=k)
    model.fit(X_train, y_train)
    train_accuracies.append(accuracy_score(y_train, model.predict(X_train)))
```

```python
    test_accuracies.append(accuracy_score(y_test, model.predict(X_test)))

# Step 2: Plot error rates
plt.plot(k_values, train_accuracies, label='Train Accuracy')
plt.plot(k_values, test_accuracies, label='Test Accuracy')
plt.xlabel('K Value')
plt.ylabel('Accuracy')
plt.legend()
plt.title('KNN Accuracy for Different K Values')
plt.show()

# Step 3: Evaluate the best model
best_k = k_values[np.argmax(test_accuracies)]
model = KNeighborsClassifier(n_neighbors=best_k)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

print(f"Best K: {best_k}")
print(f"Accuracy: {accuracy_score(y_test, y_pred)}")
print(classification_report(y_test, y_pred))
```




```
Best K: 11
Accuracy: 0.8706766917293233
              precision    recall  f1-score   support

           0       0.89      0.97      0.93       567
           1       0.62      0.31      0.41        98

    accuracy                           0.87       665
   macro avg       0.76      0.64      0.67       665
weighted avg       0.85      0.87      0.85       665
```

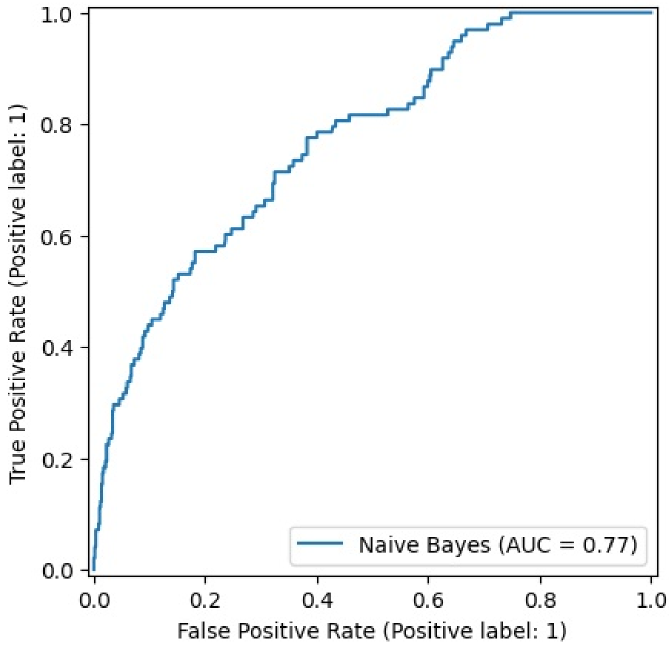
In [6]:
```python
# Step 1: Train SVM with RBF kernel
model = SVC(kernel='rbf', probability=True)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

print(f"SVM Accuracy: {accuracy_score(y_test, y_pred)}")
print(classification_report(y_test, y_pred))
```

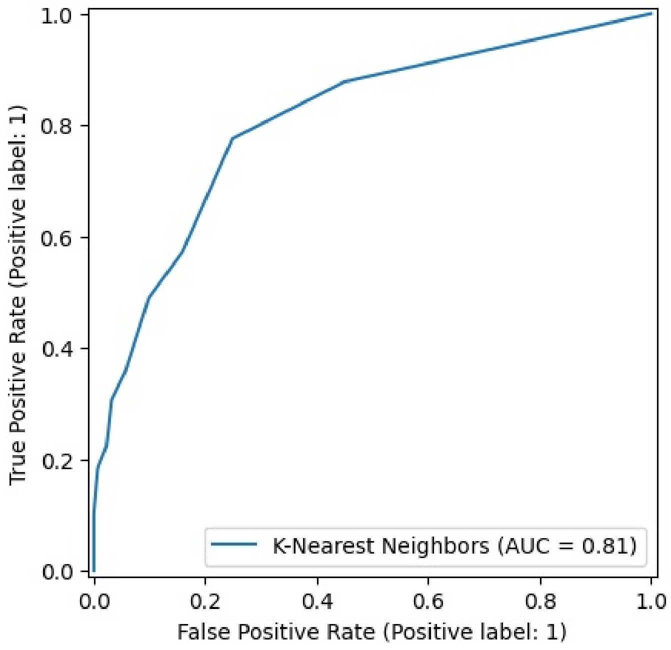
```
SVM Accuracy: 0.8646616541353384
              precision    recall  f1-score   support

           0       0.88      0.97      0.92       567
           1       0.59      0.27      0.37        98

    accuracy                           0.86       665
   macro avg       0.74      0.62      0.65       665
weighted avg       0.84      0.86      0.84       665
```

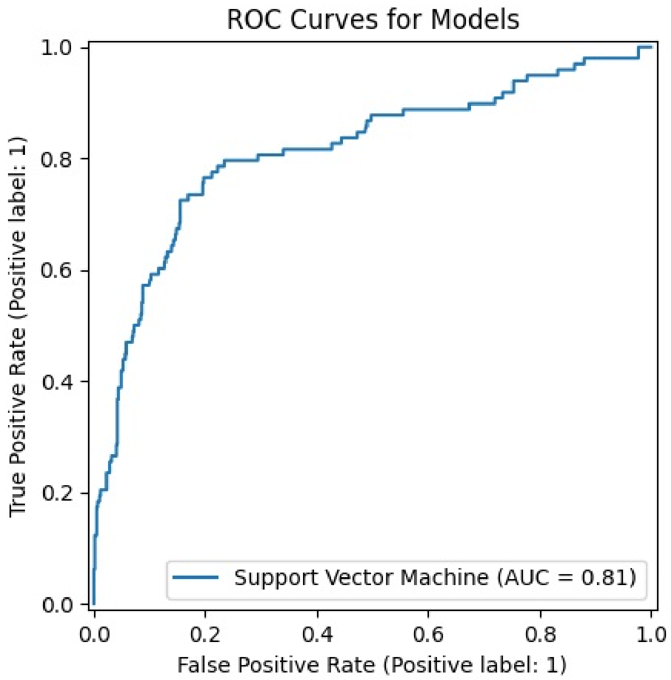
In [7]:
```python
from sklearn.metrics import accuracy_score, classification_report, roc_auc_score, RocCurveDisplay

# Function to calculate and store model performance
def evaluate_model(model_name, y_true, y_pred, y_probs=None):
    accuracy = accuracy_score(y_true, y_pred)
```

```
    report = classification_report(y_true, y_pred, output_dict=True)
    roc_auc = None
    if y_probs is not None:
        roc_auc = roc_auc_score(y_true, y_probs[:, 1])

    return {
        "Model": model_name,
        "Accuracy": accuracy,
        "Precision (Class 1)": report["1"]["precision"],
        "Recall (Class 1)": report["1"]["recall"],
        "F1-Score (Class 1)": report["1"]["f1-score"],
        "ROC-AUC": roc_auc
    }

# Train and evaluate Naive Bayes
nb_model = GaussianNB(var_smoothing=10)
nb_model.fit(X_train, y_train)
nb_y_pred = nb_model.predict(X_test)
nb_y_probs = nb_model.predict_proba(X_test)
nb_results = evaluate_model("Naive Bayes", y_test, nb_y_pred, nb_y_probs)

# Train and evaluate K-Nearest Neighbors
knn_model = KNeighborsClassifier(n_neighbors=11)
knn_model.fit(X_train, y_train)
knn_y_pred = knn_model.predict(X_test)
knn_y_probs = knn_model.predict_proba(X_test)
knn_results = evaluate_model("K-Nearest Neighbors", y_test, knn_y_pred, knn_y_probs)

# Train and evaluate Support Vector Machine
svm_model = SVC(kernel="rbf", probability=True)
svm_model.fit(X_train, y_train)
svm_y_pred = svm_model.predict(X_test)
svm_y_probs = svm_model.predict_proba(X_test)
svm_results = evaluate_model("Support Vector Machine", y_test, svm_y_pred, svm_y_probs)

# Compile results into a DataFrame
import pandas as pd

results = pd.DataFrame([nb_results, knn_results, svm_results])
print(results)

# Plot ROC curves
RocCurveDisplay.from_estimator(nb_model, X_test, y_test, name="Naive Bayes")
RocCurveDisplay.from_estimator(knn_model, X_test, y_test, name="K-Nearest Neighbors")
RocCurveDisplay.from_estimator(svm_model, X_test, y_test, name="Support Vector Machine")
plt.title("ROC Curves for Models")
plt.show()
```

```
                    Model  Accuracy  Precision (Class 1)  Recall (Class 1)  \
0             Naive Bayes  0.854135             1.000000          0.010204   
1     K-Nearest Neighbors  0.870677             0.625000          0.306122   
2  Support Vector Machine  0.864662             0.590909          0.265306   

   F1-Score (Class 1)   ROC-AUC  
0            0.020202  0.768671  
1            0.410959  0.807850  
2            0.366197  0.812169  
```







The comparison highlights the performance of three classification models (Naive Bayes, K-Nearest Neighbors, and Support Vector Machine) on predicting customer responses:

1. Accuracy K-Nearest Neighbors (KNN) achieved the highest accuracy at 87.07%, slightly outperforming the Support Vector Machine (SVM) at 86.47%, with Naive Bayes (NB) trailing at 85.41%. However, accuracy alone may not reflect model quality, especially when the dataset is imbalanced.

2. Precision (Class 1 - Positive Response) Naive Bayes: Achieved perfect precision (1.00), meaning all predicted positive responses were correct. However, its low recall indicates it predicted very few positives overall.

KNN: Precision is 62.5%, suggesting moderate reliability in identifying true positives.

SVM: Precision is 59.1%, slightly lower than KNN but still indicating reasonable performance.

3. Recall (Class 1 - Positive Response) Naive Bayes: Extremely low recall (1.02%), meaning it identified almost none of the actual positive responses. This indicates a bias toward predicting negatives.

KNN: Recall is 30.61%, showing it captures more true positives than Naive Bayes but still misses many.

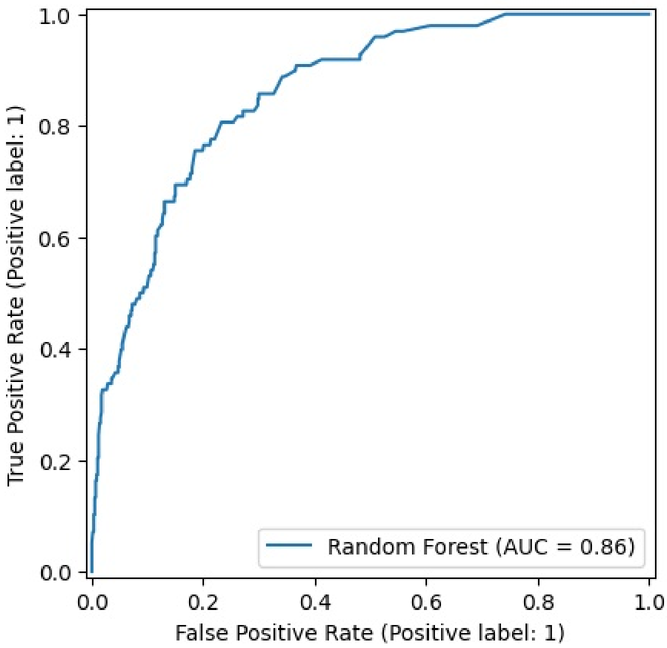
SVM: Recall is slightly lower at 26.53%, showing it is less sensitive to identifying actual positives compared to KNN.

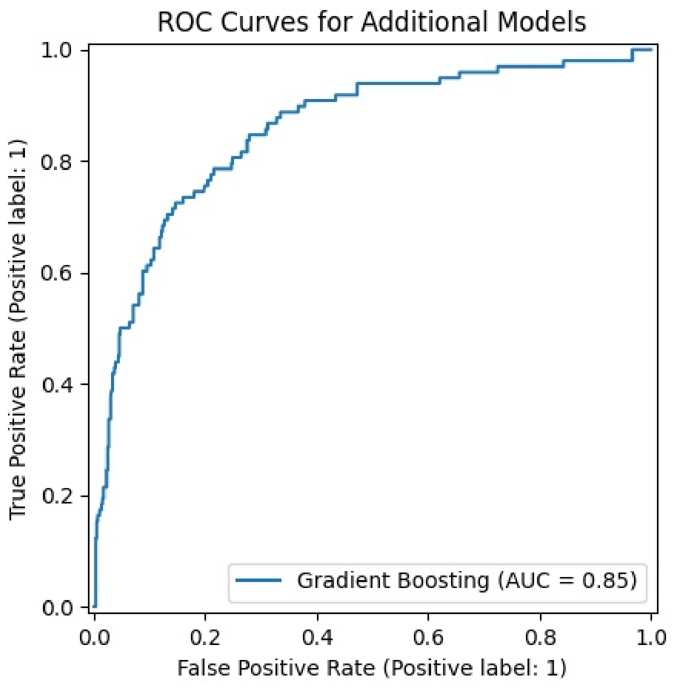
4. F1-Score (Class 1) F1-Score balances precision and recall: Naive Bayes: Extremely low F1-Score (0.02) due to its poor recall, despite perfect precision. KNN: Highest F1-Score (0.41), indicating a better trade-off between precision and recall. SVM: Slightly lower F1-Score (0.37), suggesting it is less balanced than KNN for identifying positive responses.

5. ROC-AUC Measures the overall ability of the model to distinguish between classes: Naive Bayes: Lowest ROC-AUC (0.7687), suggesting poor separation between positive and negative responses. KNN: Improved performance with an ROC-AUC of 0.8078, indicating it is better at distinguishing between the two classes. SVM: Best ROC-AUC (0.8122), showing the strongest class separation overall.

In [8]:
```
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.metrics import accuracy_score, classification_report, roc_auc_score, RocCurveDisplay

# Function to evaluate a model
def evaluate_model(model_name, model, X_train, y_train, X_test, y_test):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    y_probs = model.predict_proba(X_test)

    accuracy = accuracy_score(y_test, y_pred)
    report = classification_report(y_test, y_pred, output_dict=True)
    roc_auc = roc_auc_score(y_test, y_probs[:, 1])

    return {
        "Model": model_name,
        "Accuracy": accuracy,
        "Precision (Class 1)": report["1"]["precision"],
        "Recall (Class 1)": report["1"]["recall"],
        "F1-Score (Class 1)": report["1"]["f1-score"],
        "ROC-AUC": roc_auc
    }

# Train and evaluate Random Forest
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_results = evaluate_model("Random Forest", rf_model, X_train, y_train, X_test, y_test)

# Train and evaluate Gradient Boosting
gb_model = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, random_state=42)
gb_results = evaluate_model("Gradient Boosting", gb_model, X_train, y_train, X_test, y_test)

# Compile results into a DataFrame
additional_results = pd.DataFrame([rf_results, gb_results])
print(additional_results)

# Plot ROC curves for the additional models
RocCurveDisplay.from_estimator(rf_model, X_test, y_test, name="Random Forest")
RocCurveDisplay.from_estimator(gb_model, X_test, y_test, name="Gradient Boosting")
plt.title("ROC Curves for Additional Models")
plt.show()
```

```
               Model  Accuracy  Precision (Class 1)  Recall (Class 1)  \
0      Random Forest  0.878195             0.673469          0.336735   
1  Gradient Boosting  0.882707             0.672414          0.397959   

   F1-Score (Class 1)   ROC-AUC  
0             0.44898  0.859599  
1             0.50000  0.854911  
```





Accuracy:

Gradient Boosting (88.27%) slightly outperformed Random Forest (87.82%), but both are competitive with earlier models.

Precision (Class 1):

Both Random Forest and Gradient Boosting models achieved similar precision (~67%), indicating reliable identification of true positives among predicted positives.

Recall (Class 1):

Gradient Boosting had higher recall (39.8%) compared to Random Forest (33.7%), meaning it identified more actual positive responses, albeit still missing many.

F1-Score (Class 1):

Gradient Boosting achieved the highest F1-Score (0.50), suggesting the best balance between precision and recall among all models tested.

ROC-AUC:

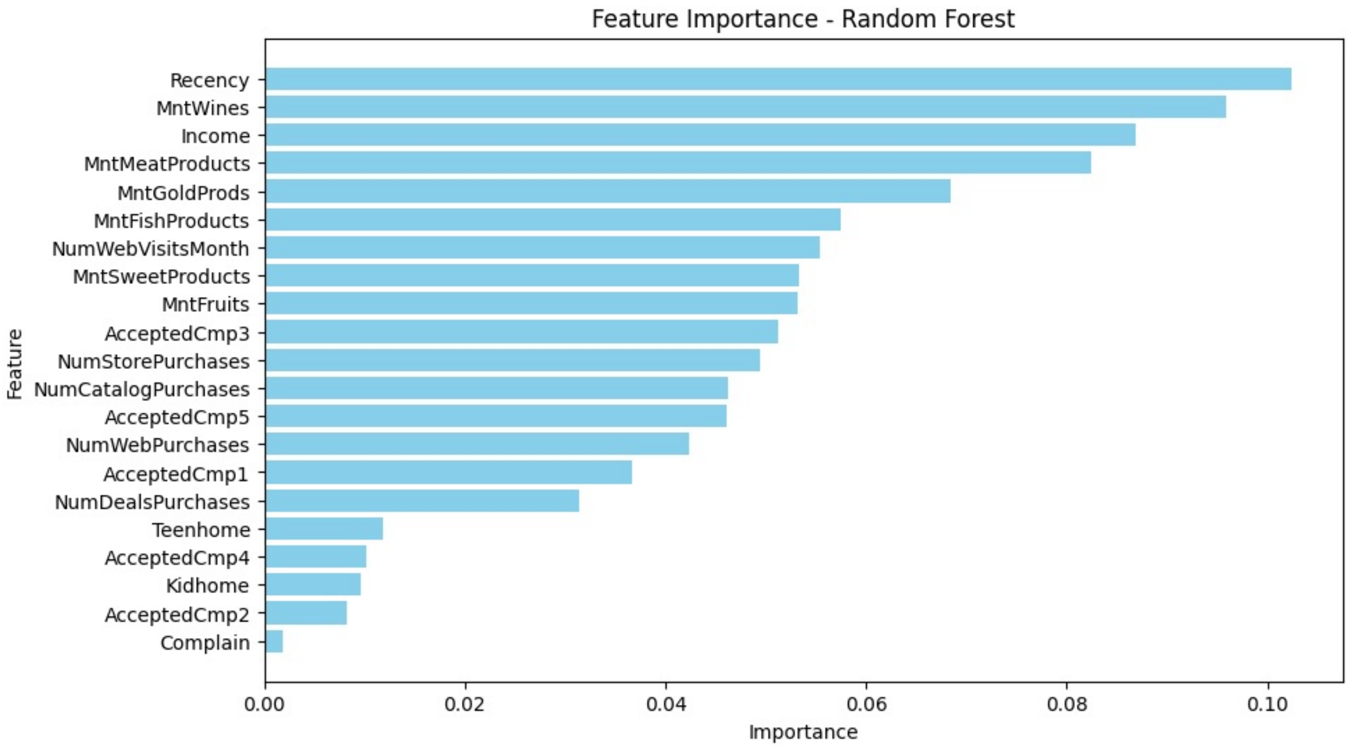
Random Forest achieved a slightly better ROC-AUC (0.860) compared to Gradient Boosting (0.855), indicating slightly better discrimination between classes.

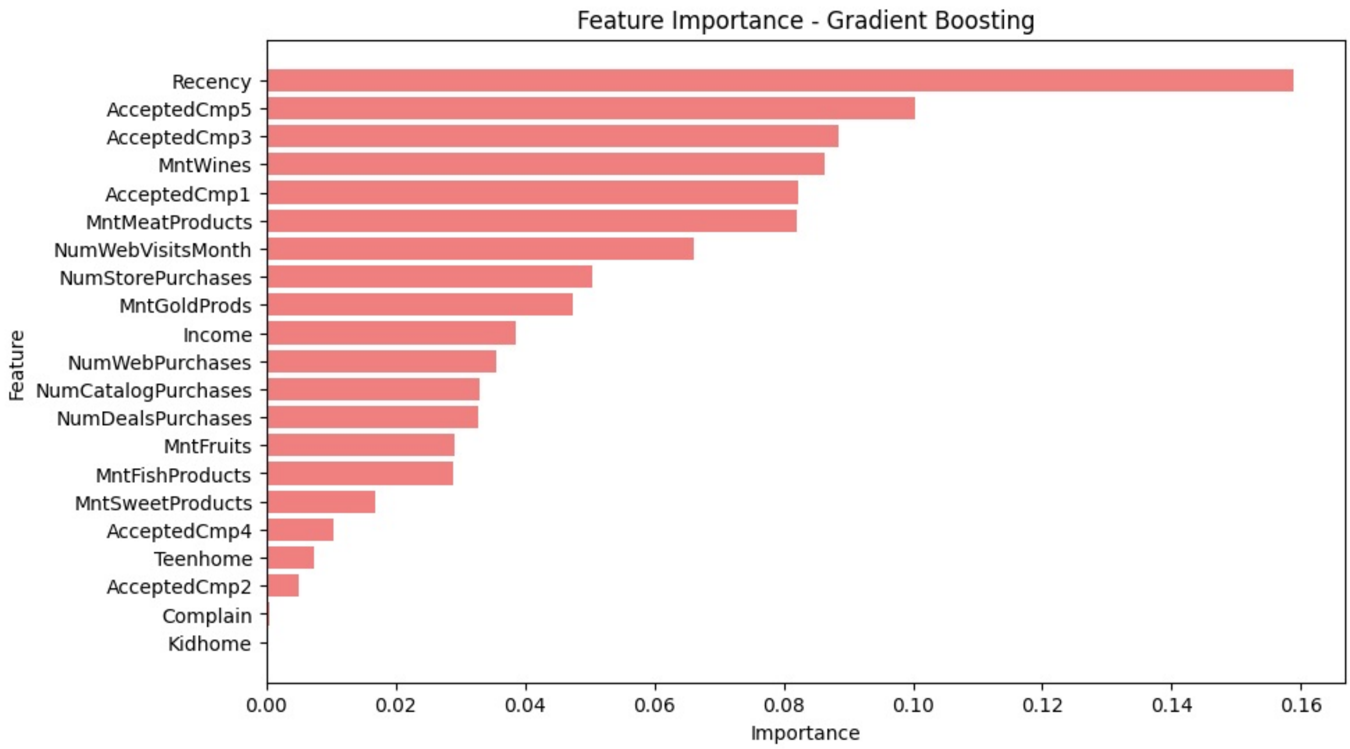
Insight: Gradient Boosting emerges as the most balanced model overall, with the highest F1-Score and competitive performance in accuracy, precision, and recall.

Random Forest is slightly less balanced but remains robust, achieving the highest ROC-AUC among all models.

In [11]:
```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np

feature_names = df.drop('Response', axis=1).columns

# Extract feature importance from Random Forest
rf_importance = rf_model.feature_importances_
rf_features = pd.DataFrame({
    'Feature': feature_names,
    'Importance': rf_importance
}).sort_values(by='Importance', ascending=False)

# Extract feature importance from Gradient Boosting
gb_importance = gb_model.feature_importances_
gb_features = pd.DataFrame({
    'Feature': feature_names,
    'Importance': gb_importance
```

```python
}).sort_values(by='Importance', ascending=False)

# Plot feature importance for Random Forest
plt.figure(figsize=(10, 6))
plt.barh(rf_features['Feature'], rf_features['Importance'], color='skyblue')
plt.gca().invert_yaxis()
plt.title('Feature Importance - Random Forest')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()

# Plot feature importance for Gradient Boosting
plt.figure(figsize=(10, 6))
plt.barh(gb_features['Feature'], gb_features['Importance'], color='lightcoral')
plt.gca().invert_yaxis()
plt.title('Feature Importance - Gradient Boosting')
plt.xlabel('Importance')
plt.ylabel('Feature')
plt.show()

# Combine and compare feature importance
combined_importance = pd.DataFrame({
    'Feature': feature_names,
    'Random Forest Importance': rf_importance,
    'Gradient Boosting Importance': gb_importance
}).sort_values(by='Gradient Boosting Importance', ascending=False)

print(combined_importance)
```




Feature Importance - Gradient Boosting
Recency
AcceptedCmp5
AcceptedCmp3
MntWines
AcceptedCmp1
MntMeatProducts
NumWebVisitsMonth
NumStorePurchases
MntGoldProds
Income
NumWebPurchases
NumCatalogPurchases
NumDealsPurchases
MntFruits
MntFishProducts
MntSweetProducts
AcceptedCmp4
Teenhome
AcceptedCmp2
Complain
Kidhome
Feature
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16
Importance

```
                Feature  Random Forest Importance  \
3               Recency                  0.102404
17         AcceptedCmp5                  0.046092
15         AcceptedCmp3                  0.051166
4              MntWines                  0.095847
18         AcceptedCmp1                  0.036607
6       MntMeatProducts                  0.082419
14    NumWebVisitsMonth                  0.055377
13    NumStorePurchases                  0.049381
9          MntGoldProds                  0.068493
0                Income                  0.086866
11      NumWebPurchases                  0.042387
12  NumCatalogPurchases                  0.046164
10    NumDealsPurchases                  0.031430
5             MntFruits                  0.053112
7       MntFishProducts                  0.057473
8      MntSweetProducts                  0.053252
16         AcceptedCmp4                  0.010163
2              Teenhome                  0.011891
19         AcceptedCmp2                  0.008168
20             Complain                  0.001767
1               Kidhome                  0.009543

    Gradient Boosting Importance
3                       0.158811
17                      0.100348
15                      0.088513
4                       0.086274
18                      0.082194
6                       0.081926
14                      0.066115
13                      0.050384
9                       0.047374
0                       0.038633
11                      0.035632
12                      0.032902
10                      0.032821
5                       0.029004
7                       0.028891
8                       0.016813
16                      0.010470
2                       0.007453
19                      0.004938
20                      0.000503
1                       0.000000
```

Targeted Marketing Strategy Based on Feature Insights

Based on the feature importance analysis, we can develop a focused marketing strategy that targets the most relevant customer segments for the upcoming product launch.

1. Customer Segmentation

A. High Engagement Customers (Recent Purchasers)

Target Group: Customers with low Recency (i.e., recent purchasers). Insight: Customers who have made recent purchases are highly likely to respond to new product offers. Marketing Strategy: Personalized Offers: Send personalized email campaigns or push notifications highlighting the new product, offering a special discount or exclusive pre-order deal. Loyalty Programs: Engage them with loyalty points for making a purchase of the new product or for referring a friend.

B. Repeat Campaign Responders

Target Group: Customers who accepted past campaigns (AcceptedCmp1, AcceptedCmp3, AcceptedCmp5). Insight: These customers have shown a higher likelihood of responding to marketing campaigns, which means they are already familiar with the company's offerings. Marketing Strategy: VIP Campaigns: Offer exclusive access to the new product, such as early bird promotions or limited-time bundles. Customer Journey Mapping: Personalize offers based on the previous campaigns they responded to, emphasizing how the new product aligns with their past preferences.

C. High-Spending Customers (High Spend on Specific Products)

Target Group: Customers who have spent significantly on MntWines, MntMeatProducts, MntFishProducts, and MntGoldProds. Insight: Customers with high spending in specific product categories are more likely to respond to the new product if it aligns with their interests. Marketing Strategy: Product Bundling: Bundle the new product with their most frequently purchased items, like a wine package or meat products, to increase purchase likelihood. Upsell Strategy: Promote the new product as a premium option for those who typically spend more on high-value items.

D. Frequent Online Shoppers

Target Group: Customers with a high number of NumWebVisitsMonth, NumWebPurchases, and NumStorePurchases. Insight: These customers are highly engaged with the website and have a strong purchasing behavior across online channels. Marketing Strategy: Retargeting Campaigns: Utilize targeted retargeting ads to remind these customers of the new product they might be interested in. Exclusive Online Discounts: Offer them special online-only promotions or free shipping to incentivize quick adoption of the new product.

2. Marketing Channels

A. Email Campaigns

Target: High engagement customers and repeat campaign responders. Content: Highlight the product's benefits, introduce exclusive offers for loyal customers, and encourage quick adoption with time-limited discounts.

B. Social Media and Digital Advertising

Target: Frequent online shoppers and high spenders on specific products. Content: Use visually rich content (e.g., videos and carousel ads) to showcase how the new product fits into their existing purchase habits. Leverage paid social media ads for retargeting based on website visits.

C. Website Personalization

Target: Frequent web visitors and high-spending customers. Content: Use personalized product recommendations based on their previous purchasing history (e.g., "Since you bought wine frequently, check out our latest wine-related product!").

D. Loyalty Program

Target: All customers who show high engagement or high spend. Content: Offer loyalty points for interacting with the campaign, making purchases, or referring the product to others.

3. Messaging and Offers

A. Exclusive Offers for High Engagement Segments

Offer Type: Early access or exclusive discounts for customers who are recent or repeat responders to campaigns. Message: "As one of our most loyal customers, we want to offer you early access to our new product launch! Get an exclusive 20% discount for the next 48 hours."

B. Upsell and Cross-Sell for High-Spending Segments

Offer Type: Premium product bundles for customers who have spent significantly on wine, meat, or other categories. Message: "We've curated a special bundle just for you, combining our new product with the best of what you love. Save 15% when you purchase today!"

C. Retargeting for Frequent Web Visitors

Offer Type: Online-exclusive deals or free shipping for customers who are frequent online shoppers. Message: "We noticed you've been browsing our site—why not take the next step? Enjoy free shipping on your order today!"

4. Measurement & Adjustments

A. KPIs to Track:

Conversion Rate: Measure how many targeted customers are making a purchase based on the personalized campaign. Customer Retention Rate: Track the loyalty of customers who responded to the campaign and return for future purchases. Average Order Value (AOV): Measure how the targeted promotions (e.g., product bundles) affect overall spending.

B. Optimization:

Regularly analyze the campaign performance and adjust the messaging based on which segments are responding best. Test different offers or product bundles to see what resonates most with each segment.

5. Budget Allocation

High-Engagement Segments (Recent Purchasers): Allocate a higher percentage of the budget for exclusive offers or early access campaigns. Frequent Online Shoppers: Invest in retargeting ads and exclusive online deals. High-Spending Customers: Allocate a budget for premium product bundles or VIP loyalty programs.

Summary

By focusing on high-engagement customers, repeat campaign responders, and those with specific spending habits, this strategy tailors marketing efforts to customers who are most likely to respond. The use of personalized offers, targeted digital campaigns, and loyalty programs maximizes the chances of successfully launching the new product.