In [86]:
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import numpy as np
import seaborn as sns
```

In [87]:
```
df = pd.read_excel('Online Retail.xlsx')

df.head()
```

Out[87]:

| | InvoiceNo | StockCode | Description | Quantity | InvoiceDate | UnitPrice | CustomerID | Cou |
|---|---|---|---|---|---|---|---|---|
| **0** | 536365 | 85123A | WHITE HANGING HEART T-LIGHT HOLDER | 6 | 2010-12-01 08:26:00 | 2.55 | 17850.0 | Un Kingc |
| **1** | 536365 | 71053 | WHITE METAL LANTERN | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 | Un Kingc |
| **2** | 536365 | 84406B | CREAM CUPID HEARTS COAT HANGER | 8 | 2010-12-01 08:26:00 | 2.75 | 17850.0 | Un Kingc |
| **3** | 536365 | 84029G | KNITTED UNION FLAG HOT WATER BOTTLE | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 | Un Kingc |
| **4** | 536365 | 84029E | RED WOOLLY HOTTIE WHITE HEART. | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 | Un Kingc |

# Online Retail Dataset Description

## Overview

This dataset from UC Irvine Machine Learning Repository contains 541,000 rows of transaction records from an online retail store, capturing details about purchases made by customers, including product information, pricing, and customer demographics.

https://archive.ics.uci.edu/dataset/352/online+retail

# Column Descriptions

- **InvoiceNo**: A unique identifier for each transaction (invoice). Multiple rows with the same `InvoiceNo` represent items from the same order.
- **StockCode**: A unique product code assigned to each item sold.
- **Description**: The name or brief description of the product.
- **Quantity**: The number of units of the product purchased in the transaction.
- **InvoiceDate**: The date and time when the transaction occurred (format: `DD/MM/YYYY HH:MM`).
- **UnitPrice**: The price per unit of the product in the transaction.
- **CustomerID**: A unique identifier assigned to each customer.
- **Country**: The country where the customer is located.

In [88]:
```
print("Amount of rows: ", df.shape[0])
print(df.isnull().sum())
```

```
Amount of rows:  541909
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135080
Country             0
dtype: int64
```

In [89]:
```
# drolling out the rows with missing values
df = df.dropna()
```

In [90]:
```
# drop unnecessary columns
df = df.drop(['StockCode', 'Description', 'Country'], axis=1)

df.head()
```

Out[90]:

| | InvoiceNo | Quantity | InvoiceDate | UnitPrice | CustomerID |
|---|---|---|---|---|---|
| **0** | 536365 | 6 | 2010-12-01 08:26:00 | 2.55 | 17850.0 |
| **1** | 536365 | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 |
| **2** | 536365 | 8 | 2010-12-01 08:26:00 | 2.75 | 17850.0 |
| **3** | 536365 | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 |
| **4** | 536365 | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 |

In [91]:
```
df['TotalSpend'] = df['Quantity'] * df['UnitPrice']

df.head()
```

Out[91]:

| | InvoiceNo | Quantity | InvoiceDate | UnitPrice | CustomerID | TotalSpend |
|---|---|---|---|---|---|---|
| **0** | 536365 | 6 | 2010-12-01 08:26:00 | 2.55 | 17850.0 | 15.30 |
| **1** | 536365 | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 | 20.34 |
| **2** | 536365 | 8 | 2010-12-01 08:26:00 | 2.75 | 17850.0 | 22.00 |
| **3** | 536365 | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 | 20.34 |
| **4** | 536365 | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 | 20.34 |

In [92]:

```
# Convert InvoiceDate to datetime format
df['InvoiceDate'] = pd.to_datetime(df['InvoiceDate'])
```

In [93]:

```
# Compute RFM metrics
rfm = df.groupby('CustomerID').agg({
    'InvoiceDate': lambda x: (df['InvoiceDate'].max() - x.max()).days,  # Recency:
    'InvoiceNo': 'nunique',  # Frequency: Number of unique purchases
    'TotalSpend': 'sum'  # Monetary Value
})
rfm.columns = ['Recency', 'Frequency', 'Monetary']

# Remove negative and NaN monetary values
rfm = rfm[rfm['Monetary'] > 0]

# Apply log transformation AFTER cleaning data
rfm['Monetary'] = np.log1p(rfm['Monetary'])
```

# Computing RFM Metrics

## Overview

RFM (Recency, Frequency, and Monetary) analysis is a customer segmentation technique that helps businesses understand purchasing behavior. It assigns customers into different groups based on their **last purchase date (Recency)**, **purchase frequency (Frequency)**, and **total spending (Monetary value)**.

## Steps:

1. **Grouping by CustomerID**
    - Transactions are grouped by `CustomerID` to analyse each customer's purchase behavior.
2. **Calculating RFM Metrics**
    - **Recency**: Measures how many days have passed since a customer's last purchase. A lower value indicates an active customer.
    - **Frequency**: Counts the number of unique purchases made by the customer. A

higher frequency suggests a loyal customer.
- **Monetary**: Represents the total spending of a customer. Higher values indicate valuable customers.

3. **Filtering Out Invalid Monetary Values**
   - Customers with **negative or zero spending** are removed to maintain data accuracy. This ensures that only customers with valid purchases are considered in the segmentation process.
4. **Applying Log Transformation**
   - Since monetary values often have extreme variations, a **log transformation** is applied to **normalise the data** and reduce skewness. This makes the clustering process more effective.

### Why Use RFM?

- **Recency** identifies customers who have recently interacted with the business.
- **Frequency** helps find repeat customers and potential brand loyalists.
- **Monetary** allows businesses to focus on high-value customers.

### Business Applications

- **Customer Retention**: Identify inactive customers and re-engage them with offers.
- **Targeted Marketing**: Segment customers based on spending behavior for personalised campaigns.
- **Loyalty Programs**: Reward frequent buyers and high-value customers.

In [94]:
```
scaler = StandardScaler()
rfm_scaled = scaler.fit_transform(rfm)
```

## Standardising RFM Metrics

### Why Standardisation?

- Ensures **Recency, Frequency, and Monetary** values are on the same scale.
- Prevents larger values (e.g., Recency in days) from dominating clustering.
- Improves **K-Means accuracy** by giving equal importance to all features.

### Method: StandardScaler

- **Removes the mean** and **scales to unit variance**.
- Transforms data so each feature has a **mean of 0** and **standard deviation of 1**.

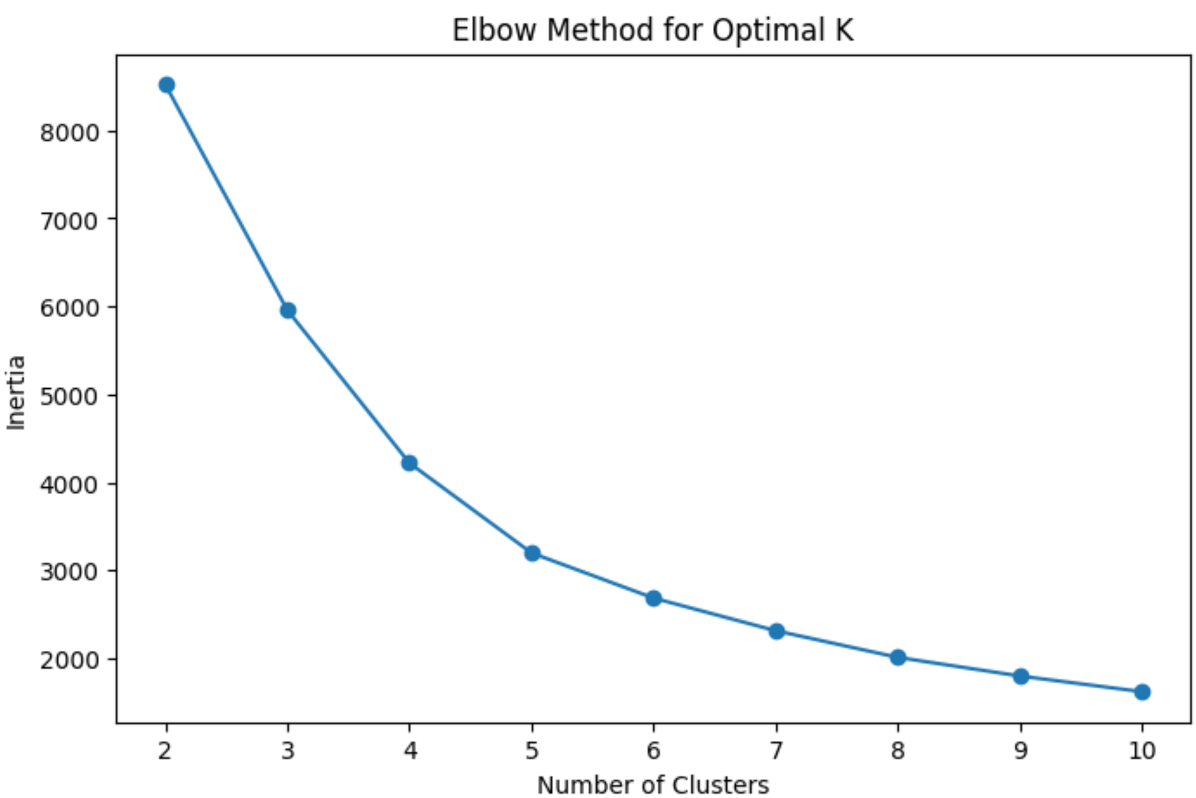
### Outcome

- Normalised RFM values for **better clustering results**.

In [95]:
```
inertia_values = []
k_range = range(2, 11)

for k in k_range:
    kmeans = KMeans(n_clusters=k, n_init=10, random_state=42)
    kmeans.fit(rfm_scaled)
    inertia_values.append(kmeans.inertia_)

# Plot the Elbow Method
plt.figure(figsize=(8, 5))
plt.plot(k_range, inertia_values, marker='o')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.title('Elbow Method for Optimal K')
plt.show()
```




# Choosing the Number of Clusters with the Elbow Method

## Overview

I used the **Elbow Method** to help find the best number of clusters (**K**) for **K-Means**. This method identifies where adding more clusters **stops significantly improving the model**.

## What I Did

- Tested **K from 2 to 10**, ran K-Means, and recorded **inertia**.
- Plotted **inertia vs. number of clusters** to find the **"elbow" point**.

### Key Takeaways

- The **"elbow" is where inertia stops dropping steeply**.
- The graph **drops fast** until **K=4**, then levels off.
- **K=4 or K=5** seems optimal, balancing accuracy and efficiency.

In [101…

```
from sklearn.metrics import silhouette_score

for k in [2, 3, 4, 5, 6]:
    kmeans = KMeans(n_clusters=k, n_init=10, random_state=42)
    labels = kmeans.fit_predict(rfm_scaled)
    score = silhouette_score(rfm_scaled, labels)
    print(f'K={k}, Silhouette Score={score:.4f}')
```

```
K=2, Silhouette Score=0.3727
K=3, Silhouette Score=0.4248
K=4, Silhouette Score=0.4156
K=5, Silhouette Score=0.4092
K=6, Silhouette Score=0.3655
```

# Silhouette Score

The **Silhouette Score** measures how well data points fit into their assigned clusters. It ranges from **-1 to 1**:

- **Closer to 1** → Well-separated clusters
- **Around 0** → Overlapping clusters
- **Below 0** → Poor clustering

## Key Findings

- **K=3 gives the best clustering** with a **Silhouette Score of 0.4248**.
- **K=4 and K=5** perform similarly but don't improve separation.
- **K=6 performs the worst**, causing overlapping clusters.

from my research the 0.42 score is moderate but not great

In [120…

```
# Apply K-Means with the chosen number of clusters
kmeans = KMeans(n_clusters=3, n_init=10, random_state=42)
rfm['Cluster'] = kmeans.fit_predict(rfm_scaled)
```

In [121…

```
# View the characteristics of each cluster
cluster_summary = rfm.groupby('Cluster').agg({
    'Recency': 'mean',
```

```
    'Frequency': 'mean',
    'Monetary': 'mean'
}).round(2)

print(cluster_summary)
```

```
         Recency  Frequency  Monetary
Cluster
0          22.95      14.95      8.32
1          47.57       2.98      6.34
2         246.77       1.70      5.58
```

# Cluster Characteristics

To understand the differences between customer groups, I calculated the **average Recency, Frequency, and Monetary values** for each cluster.

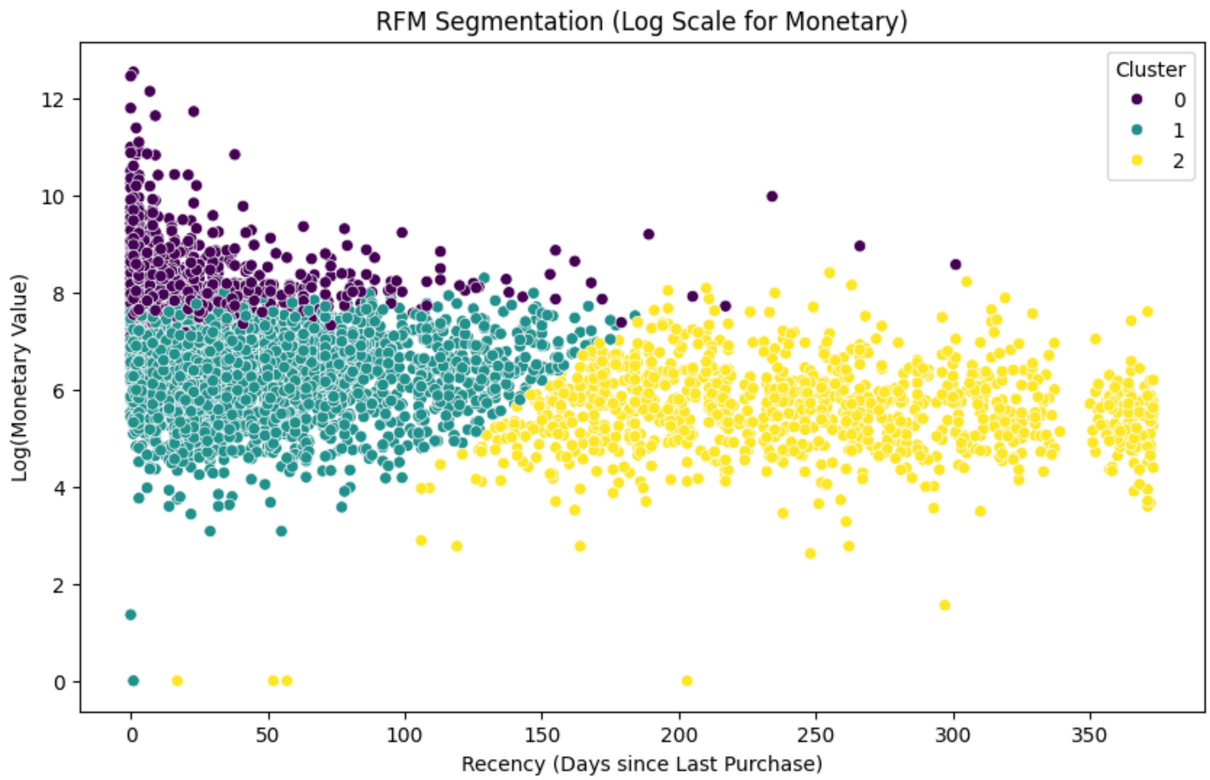
- **Recency**: Average days since the last purchase.
- **Frequency**: Average number of unique purchases.
- **Monetary**: Average total spending (log-transformed).

## Interpretation

- **Cluster 0**: Recent, frequent, and high spenders.
- **Cluster 1**: Moderate recency, lower frequency, moderate spenders.
- **Cluster 2**: Long recency, infrequent, and low spenders.

In [122…

```
plt.figure(figsize=(10, 6))
sns.scatterplot(x=rfm['Recency'], y=rfm['Monetary'], hue=rfm['Cluster'], palette='v
plt.xlabel('Recency (Days since Last Purchase)')
plt.ylabel('Log(Monetary Value)')
plt.title('RFM Segmentation (Log Scale for Monetary)')
plt.show()
```




This scatter plot visualises customer segmentation using Recency and Monetary Value.

## Cluster Insights

- **X-axis (Recency)**: Low values = recent buyers, high values = inactive customers.
- **Y-axis (Log(Monetary))**: Higher values = high spenders.
- **Cluster 0 (Purple)** → Recent, High-Spending Customers
- **Cluster 1 (Teal)** → Moderate Recency & Spending
- **Cluster 2 (Yellow)** → Inactive Customers with Low to Moderate Spending

## Issues with the Graph

The graph is ok but the Clusters (mostly purple and teal) overlap too much and the yellow spreads too much