Task 3

In [1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import davies_bouldin_score, silhouette_score, calinski_haraba
```

In [2]:
```
customers = pd.read_csv('Customers.csv')
transactions = pd.read_csv('Transactions.csv')
customer_data = pd.merge(customers, transactions, on='CustomerID')
```

In [4]:
```
customer_data.head()
```

Out[4]:

	CustomerID	CustomerName	Region	SignupDate	TransactionID	ProductID	TransactionDate
0	C0001	Lawrence Carroll	South America	2022-07-10	T00015	P054	2024-01-19 03:12:55
1	C0001	Lawrence Carroll	South America	2022-07-10	T00932	P022	2024-09-17 09:01:18
2	C0001	Lawrence Carroll	South America	2022-07-10	T00085	P096	2024-04-08 00:01:00
3	C0001	Lawrence Carroll	South America	2022-07-10	T00445	P083	2024-05-07 03:11:44
4	C0001	Lawrence Carroll	South America	2022-07-10	T00436	P029	2024-11-02 17:04:16

In [5]:
```
#Total spending per customer
customer_data['TotalSpending'] = customer_data['Quantity'] * customer_data['Price']
total_spending = customer_data.groupby('CustomerID')['TotalSpending'].sum().reset_i
total_spending
```

Out[5]:

	CustomerID	TotalSpending
0	C0001	3354.52
1	C0002	1862.74
2	C0003	2725.38
3	C0004	5354.88
4	C0005	2034.24
...	...	...
194	C0196	4982.88
195	C0197	1928.65
196	C0198	931.83
197	C0199	1979.28
198	C0200	4758.60

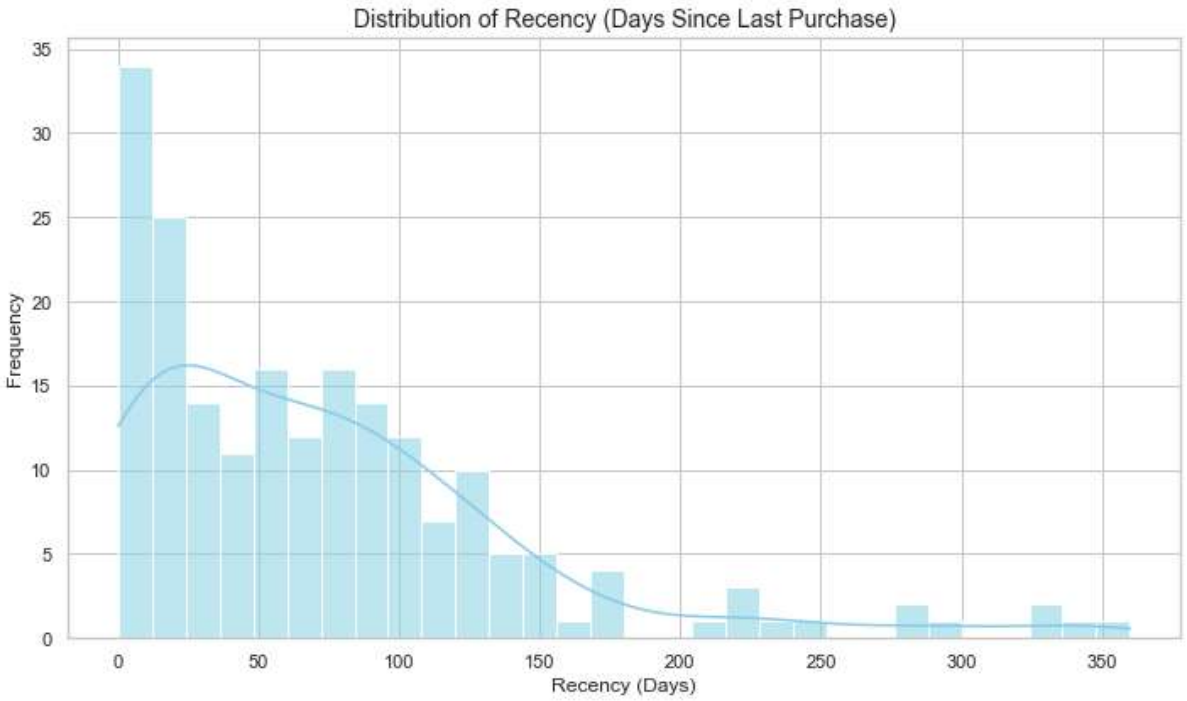
199 rows × 2 columns

In [17]:
```
#RFM features
customer_data['TransactionDate'] = pd.to_datetime(customer_data['TransactionDate'])
recent_date = customer_data['TransactionDate'].max()
customer_data['Recency'] = (recent_date - customer_data['TransactionDate']).dt.days
rfm = customer_data.groupby('CustomerID').agg({'Recency': 'min', 'TransactionID': '
rfm.rename(columns={'TransactionID': 'Frequency', 'TotalSpending': 'Monetary'}, inp
rfm.head()
```

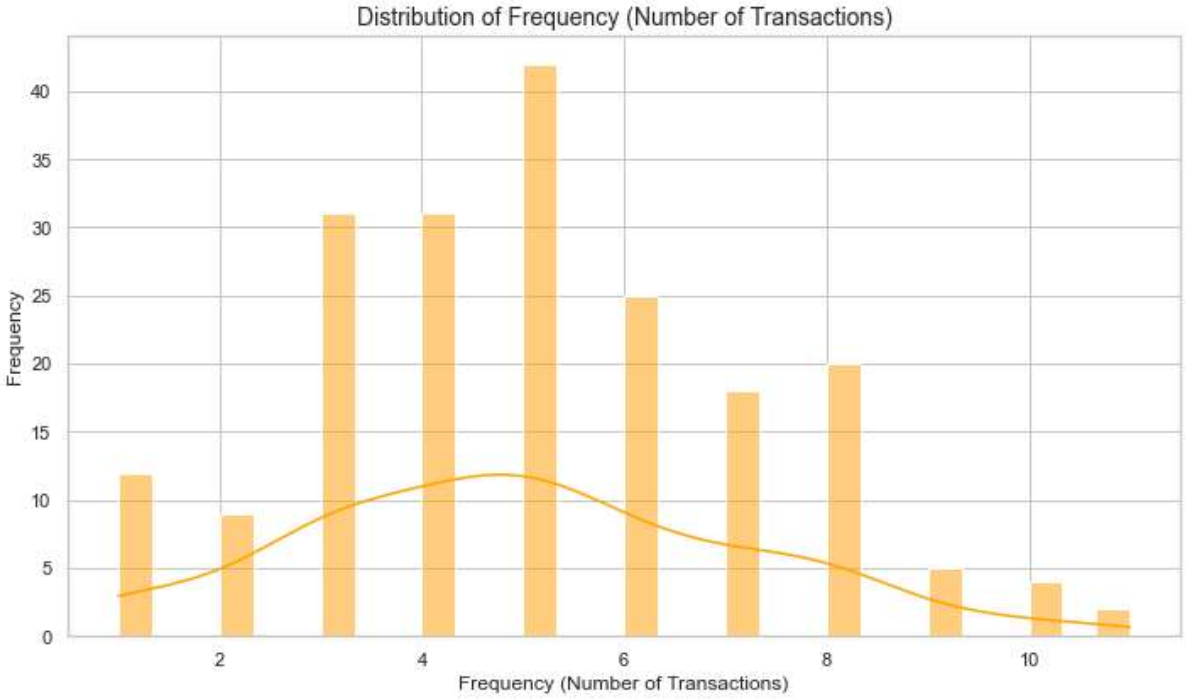
Out[17]:

CustomerID	Recency	Frequency	Monetary
C0001	55	5	3354.52
C0002	25	4	1862.74
C0003	125	4	2725.38
C0004	4	8	5354.88
C0005	54	3	2034.24

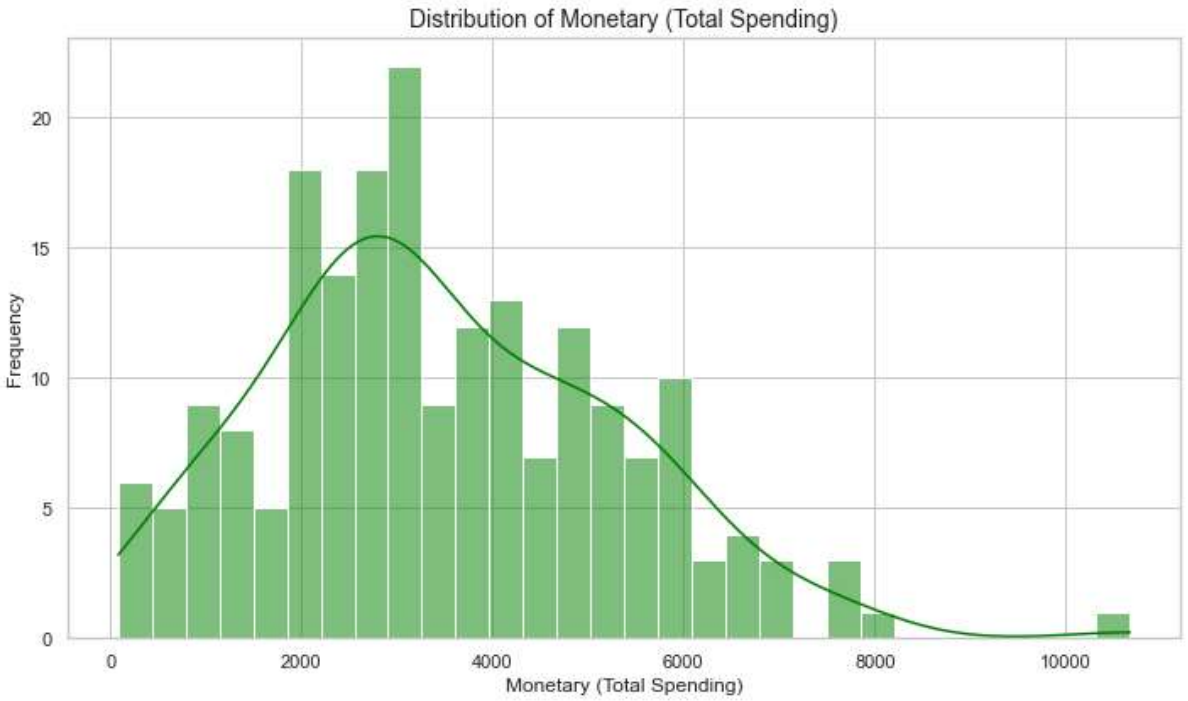
In [18]:
```
sns.set(style="whitegrid")

#Recency
plt.figure(figsize=(10, 6))
sns.histplot(rfm['Recency'], bins=30, kde=True, color='skyblue')
plt.title('Distribution of Recency (Days Since Last Purchase)', fontsize=14)
plt.xlabel('Recency (Days)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.tight_layout()
plt.show()
```



In [19]:
```
#Frequency
plt.figure(figsize=(10, 6))
sns.histplot(rfm['Frequency'], bins=30, kde=True, color='orange')
plt.title('Distribution of Frequency (Number of Transactions)', fontsize=14)
plt.xlabel('Frequency (Number of Transactions)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.tight_layout()
plt.show()
```



In [20]:
```
#Monetary
plt.figure(figsize=(10, 6))
sns.histplot(rfm['Monetary'], bins=30, kde=True, color='green')
plt.title('Distribution of Monetary (Total Spending)', fontsize=14)
plt.xlabel('Monetary (Total Spending)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.tight_layout()
plt.show()
```



In [16]:
```
#Merge features
customer_profiles = pd.merge(customers, rfm, on='CustomerID')
customer_profiles = customer_profiles.set_index('CustomerID')
customer_profiles.head()
```

Out[16]:

CustomerID	CustomerName	Region	SignupDate	Recency	Frequency	Monetary
C0001	Lawrence Carroll	South America	2022-07-10	55	5	3354.52
C0002	Elizabeth Lutz	Asia	2022-02-13	25	4	1862.74
C0003	Michael Rivera	South America	2024-03-07	125	4	2725.38
C0004	Kathleen Rodriguez	South America	2022-10-09	4	8	5354.88
C0005	Laura Weber	Asia	2022-08-15	54	3	2034.24

In [34]:
```
customer_encoder = LabelEncoder()
customer_profiles['RegionEncoded'] = customer_encoder.fit_transform(customer_profil
customer_profiles = customer_profiles.dropna(subset=['Recency', 'Frequency', 'Clust
customer_profiles.head()
```

Out[34]:

CustomerID	CustomerName	Region	SignupDate	Recency	Frequency	Monetary	RegionEncodec
C0001	Lawrence Carroll	South America	2022-07-10	55	5	3354.52	3
C0002	Elizabeth Lutz	Asia	2022-02-13	25	4	1862.74	(
C0003	Michael Rivera	South America	2024-03-07	125	4	2725.38	3
C0004	Kathleen Rodriguez	South America	2022-10-09	4	8	5354.88	3
C0005	Laura Weber	Asia	2022-08-15	54	3	2034.24	(

In [24]:
```
features = ['RegionEncoded', 'Recency', 'Frequency', 'Monetary']
X = customer_profiles[features]
X.head()
```

Out[24]:

CustomerID	RegionEncoded	Recency	Frequency	Monetary
C0001	3	55	5	3354.52
C0002	0	25	4	1862.74
C0003	3	125	4	2725.38
C0004	3	4	8	5354.88
C0005	0	54	3	2034.24

In [25]:
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

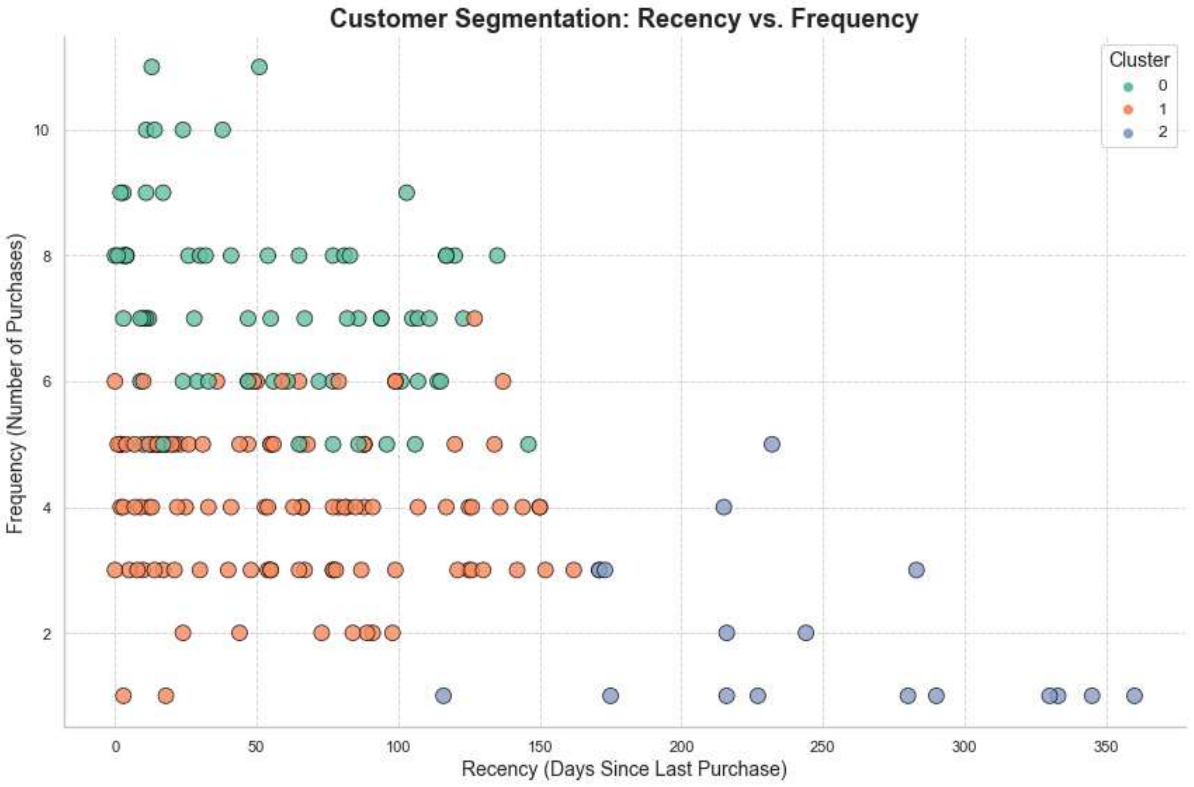
In [26]:
```
#K-Means clustering
n_clusters = 3
kmeans = KMeans(n_clusters=n_clusters, random_state=42)
customer_profiles['Cluster'] = kmeans.fit_predict(X_scaled)
```

In [27]:
```
db_index = davies_bouldin_score(X_scaled, customer_profiles['Cluster'])
silhouette = silhouette_score(X_scaled, customer_profiles['Cluster'])
calinski_harabasz = calinski_harabasz_score(X_scaled, customer_profiles['Cluster'])

print(f"DB Index: {db_index}")
print(f"Silhouette Score: {silhouette}")
print(f"Calinski-Harabasz Index: {calinski_harabasz}")
```

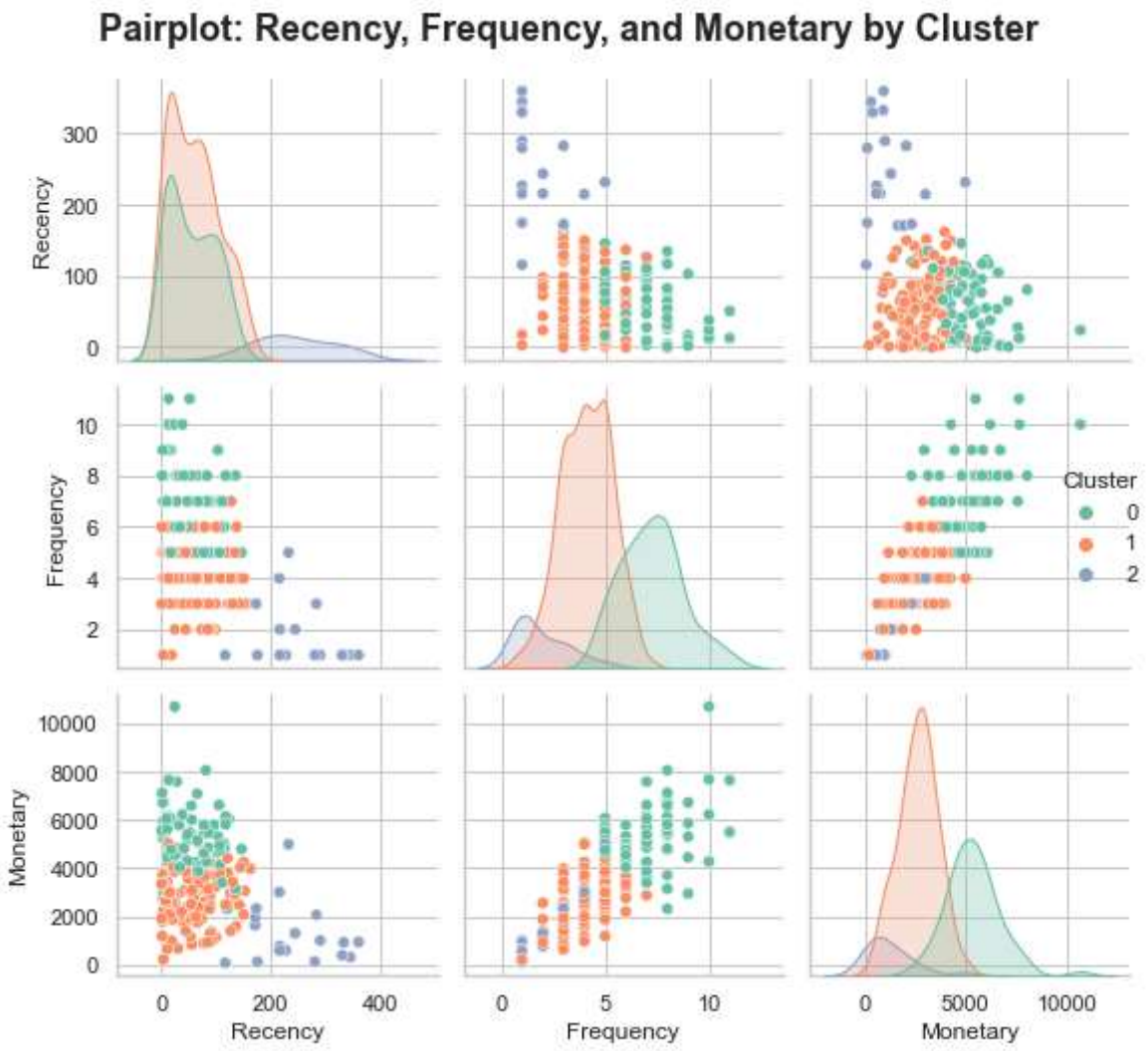
```
DB Index: 1.240165936934891
Silhouette Score: 0.2733638713438174
Calinski-Harabasz Index: 83.70696981899586
```

In [43]:
```
import matplotlib.pyplot as plt
import seaborn as sns

sns.set(style="whitegrid")

plt.figure(figsize=(12, 8))

sns.scatterplot(
    x='Recency',
    y='Frequency',
    hue='Cluster',
    data=customer_profiles,
    palette='Set2',
    s=120,
    alpha=0.8,
    edgecolor='black',
    linewidth=0.8,
)

plt.title('Customer Segmentation: Recency vs. Frequency', fontsize=18, fontweight='
plt.xlabel('Recency (Days Since Last Purchase)', fontsize=14)
plt.ylabel('Frequency (Number of Purchases)', fontsize=14)

plt.legend(title='Cluster', title_fontsize=14, fontsize=12, loc='upper right')
```

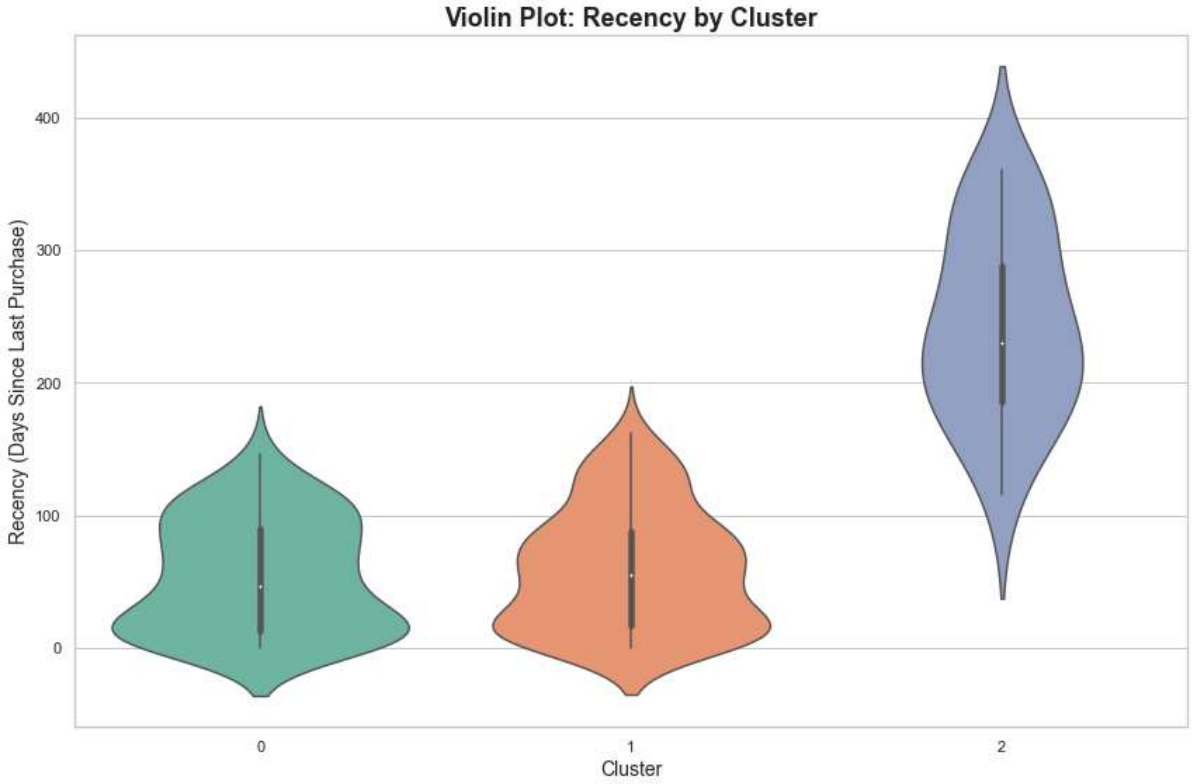
```
sns.despine()
plt.grid(True, linestyle='--', alpha=0.7, axis='both')

plt.tight_layout()

plt.show()
```

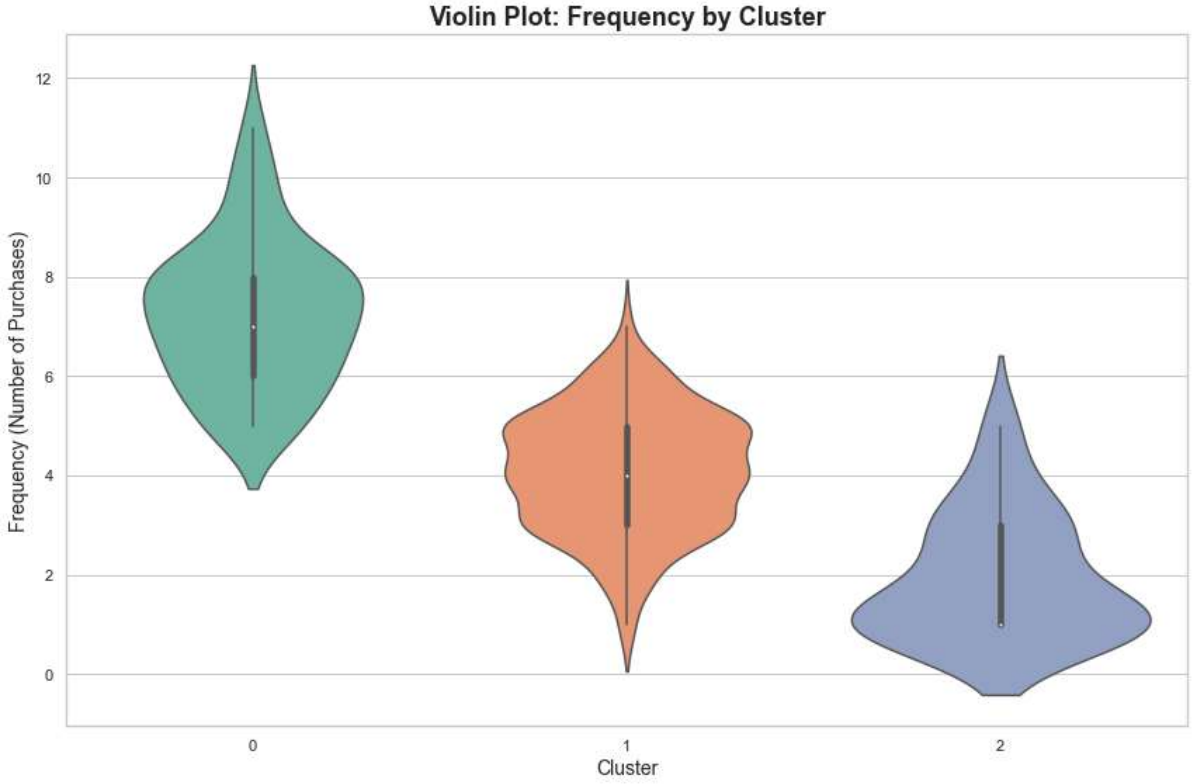


In [41]:
```
# Pairplot to show the relationships between Recency, Frequency, and Monetary
sns.pairplot(customer_profiles[['Recency', 'Frequency', 'Monetary', 'Cluster']], hu

plt.suptitle('Pairplot: Recency, Frequency, and Monetary by Cluster', fontsize=18,
plt.tight_layout()
plt.show()
```



In [42]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Violin plot for Recency by Cluster
plt.figure(figsize=(12, 8))
sns.violinplot(x='Cluster', y='Recency', data=customer_profiles, palette='Set2')

plt.title('Violin Plot: Recency by Cluster', fontsize=18, fontweight='bold')
plt.xlabel('Cluster', fontsize=14)
plt.ylabel('Recency (Days Since Last Purchase)', fontsize=14)
plt.tight_layout()
plt.show()

# Violin plot for Frequency by Cluster
plt.figure(figsize=(12, 8))
sns.violinplot(x='Cluster', y='Frequency', data=customer_profiles, palette='Set2')

plt.title('Violin Plot: Frequency by Cluster', fontsize=18, fontweight='bold')
plt.xlabel('Cluster', fontsize=14)
plt.ylabel('Frequency (Number of Purchases)', fontsize=14)
plt.tight_layout()
plt.show()
```





Report on Clustering Results:

We performed customer segmentation using clustering techniques on customer data, specifically focusing on three key features: Recency, Frequency, and Monetary. After applying the K-Means algorithm, we arrived at 3 distinct clusters. These clusters represent groups of customers with similar purchasing behaviors, allowing for targeted marketing strategies or tailored business approaches.

The Davies-Bouldin Index is a metric used to evaluate the quality of clustering by considering the dispersion within each cluster and the separation between clusters. Lower

DB Index values indicate better clustering performance. In our case, the DB Index value is computed as follows:

DB Index:1.240165936934891

Silhouette Score: Measures how similar an object is to its own cluster compared to other clusters. A score closer to 1 indicates that the clusters are well-separated and distinct.

Silhouette Score:0.2733638713438174

The Calinski-Harabasz Index (Variance Ratio Criterion) is another important clustering evaluation metric. It measures the ratio of the sum of between-cluster dispersion to within-cluster dispersion. A higher Calinski-Harabasz index indicates better-defined and well-separated clusters.

Calinski-Harabasz Index: 83.71