In [1]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

In [2]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from scipy import stats
```

In [3]:
```
file_path = '/content/drive/My Drive/Markdown Management/data_for_MarkdownMana
# file_path = 'drive/MyDrive/Markdown Management/data_for_MarkdownManagementAt
df = pd.read_excel(file_path)
```

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

Out[4]:

	ID	Branded?	Buyer	Vendor	Cost	1st Ticket Price	1st Markdown %	1st Week of Lifecycle	1st Markdown in Week #	Unite Sales by Week 3
0	1	1	1005	61	84.925	197.5	50.0	6	17.0	2.109890
1	2	0	1011	83	144.375	460.0	NaN	46	NaN	5.000000
2	3	1	1011	85	67.825	172.5	NaN	46	NaN	7.000000
3	4	1	1011	85	63.575	172.5	NaN	41	NaN	5.000000
4	5	1	1005	89	92.400	220.0	50.0	7	12.0	3.098901

In [5]:
```
new_columns = {
    'ID': 'ID','Branded?': 'Branded?','Buyer': 'Buyer','Vendor': 'Vendor','Cos
    '1st Markdown %': 'Markdown','1st Week of Lifecycle': 'Week Available','1s
    'Unite Sales by Week 3': 'Sales by Week 3','Units Sales': 'Sales','Dollar 
    'Units Salvaged': 'Units Left',
    }

df = df.rename(columns=new_columns)
df['Sunk Cost'] = (df['Units Left'] * df['Cost'])
df['Has_Markdown'] = df['Markdown'].notna()
```

Can use quintiles to track lowest 20% selling items.

There are Point of Sale Discounts also, so markdowns are needed when the product is really not moving.

Analysis reveals that sell-through in the third week of sales is a good indicator of total sell-through.

An item can complete the whole cycle in about a month, but can also be in store for upto six months (less stylish, seasonality).

Quantify how much revenue was left on the table last year in this department—and how to capture it?

In [6]:
```
df['Revenue Left'] = ((df['Sales'] * df['Initial Price']) - df['Sales Amount']
df['Sales by Week 3'] = df['Sales by Week 3'].astype(int)
df
```

Out[6]:

	ID	Branded?	Buyer	Vendor	Cost	Initial Price	Markdown	Week Available	Week of Markdown	Sales by Week 3
0	1	1	1005	61	84.925	197.50	50.0	6	17.0	2
1	2	0	1011	83	144.375	460.00	NaN	46	NaN	5
2	3	1	1011	85	67.825	172.50	NaN	46	NaN	7
3	4	1	1011	85	63.575	172.50	NaN	41	NaN	5
4	5	1	1005	89	92.400	220.00	50.0	7	12.0	3
...	...	...	...	...	...	...	...	...	...	..
4075	4076	1	1002	10	34.375	62.45	50.0	24	15.0	54
4076	4077	1	1002	45	31.875	62.45	50.0	4	24.0	2650
4077	4078	0	1003	18	11.000	24.95	NaN	2	NaN	960
4078	4079	0	1003	18	11.000	24.95	NaN	10	NaN	1674
4079	4080	0	1003	50	18.750	49.95	NaN	32	NaN	935

4080 rows × 17 columns

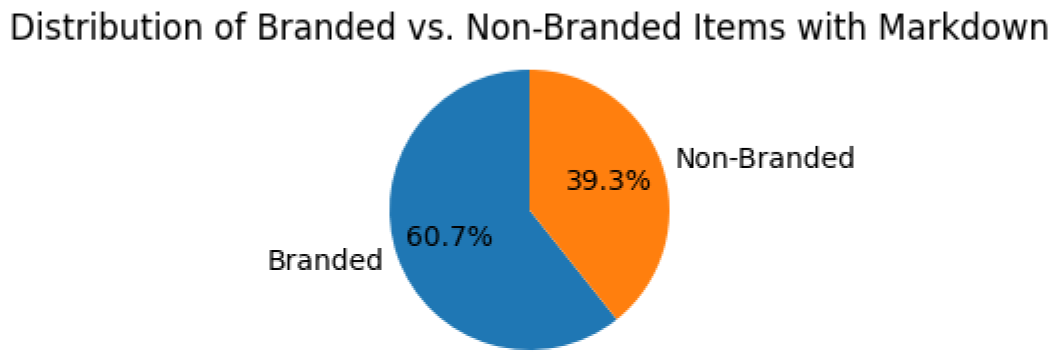
Exploratory Data Analysis -

In [7]:
```
rev_left = df.loc[df['Has_Markdown'] == True, 'Revenue Left'].sum()
print(f'Revenue left on the table last year: {round(rev_left, 2)}')
```

```
Revenue left on the table last year: 49211524.06
```

In [8]:
```
markdown_items = df.loc[df['Has_Markdown'] == True]
branded_markdown_count = markdown_items[markdown_items['Branded?'] == 1].shape
non_branded_markdown_count = markdown_items[markdown_items['Branded?'] == 0].sl

print(f"Number of branded items with markdown: {branded_markdown_count}")
print(f"Number of non-branded items with markdown: {non_branded_markdown_count

categories = ['Branded', 'Non-Branded']
counts = [branded_markdown_count, non_branded_markdown_count]
plt.figure(figsize=(4, 2))
plt.pie(counts, labels=categories, autopct='%1.1f%%', startangle=90, colors=['
plt.axis('equal')
plt.title('Distribution of Branded vs. Non-Branded Items with Markdown')
plt.show()
```

```
Number of branded items with markdown: 1385
Number of non-branded items with markdown: 896
```



In [9]:
```
def plot_analysis(df, variable):
    plt.figure(figsize=(16, 6))
    bars = df['Percentage Markdown'].plot(kind='bar', color='coral', width=0.8
    plt.title('Percentage of Items with Markdown by Vendor')
    plt.xlabel(variable)
    plt.ylabel('Percentage (%)')
    plt.legend()
    plt.xticks(rotation=45, ha='right')
    plt.grid(axis='y', alpha=0.7)
    plt.tight_layout()
    plt.show()
```

Vendor Specific Analysis -

In [10]:
```
vendor_markdown_data = df.groupby(['Vendor', 'Has_Markdown']).size().unstack(f

vendor_markdown_data.columns = ['No Markdown', 'Has Markdown']
vendor_markdown_data['Total'] = vendor_markdown_data.sum(axis=1)
vendor_markdown_data['Percentage Markdown'] = (vendor_markdown_data['Has Markd

sales_units_by_vendor_markdown = df.groupby(['Vendor', 'Has_Markdown'])[['Sale
vendor_markdown_data['Units Sold'] = df.groupby('Vendor')['Sales'].sum()
vendor_markdown_data['Units Left'] = df.groupby('Vendor')['Units Left'].sum()
vendor_markdown_data['Total Units'] = vendor_markdown_data['Units Sold'] + ven

vendor_markdown_data = vendor_markdown_data.sort_values('Percentage Markdown',
vendor_markdown_data
```

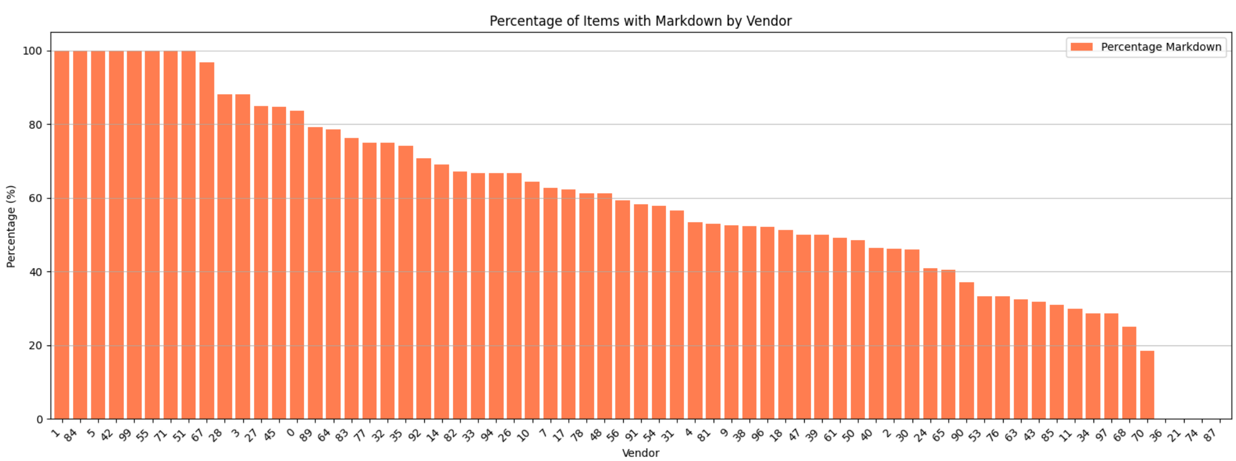
Out[10]:

Vendor	No Markdown	Has Markdown	Total	Percentage Markdown	Units Sold	Units Left	Total Units
1	0	5	5	100.000000	4412	565	4977
84	0	8	8	100.000000	1431	1385	2816
5	0	4	4	100.000000	4549	914	5463
42	0	3	3	100.000000	2840	27	2867
99	0	43	43	100.000000	56802	19163	75965
...	...	...	...	...	...	...	...
70	44	10	54	18.518519	36922	61067	97989
36	1	0	1	0.000000	28	114	142
21	5	0	5	0.000000	2405	7212	9617
74	4	0	4	0.000000	1915	2782	4697
87	1	0	1	0.000000	84	60	144

65 rows × 7 columns

In [11]:

```
plot_analysis(vendor_markdown_data, variable='Vendor')
high_markdown_vendors = vendor_markdown_data[vendor_markdown_data['Percentage M

print("Vendors with >85% units markdown and their total units:")
print(high_markdown_vendors)

total_units = vendor_markdown_data[vendor_markdown_data['Percentage Markdown']
print(f"\nSum total of units for vendors with >85% markdown: {total_units:,.0f}
```




```
Vendors with >85% units markdown and their total units:
{1: 4977, 84: 2816, 5: 5463, 42: 2867, 99: 75965, 55: 1049, 71: 20206, 51: 172
0, 67: 42878, 28: 13992, 3: 11377}

Sum total of units for vendors with >85% markdown: 308,602
```

In [12]:

```
df['% LC comp. b M'] = (df['Week of Markdown'] / df['Total Lifecycle'])
df['% Inv. sold by W3'] = (df['Sales by Week 3'] / (df['Sales'] + df['Units Le
df['% Inv. sold'] = (df['Sales'] / (df['Sales'] + df['Units Left']))
df['Price Markup'] = (df['Initial Price'] / (df['Cost']))
```

```
df["Sales Percentage"] = (df["Sales Amount"] / df["Sales Amount"].sum())
df['Markdown'] = (df['Markdown'] / 100)
df
```

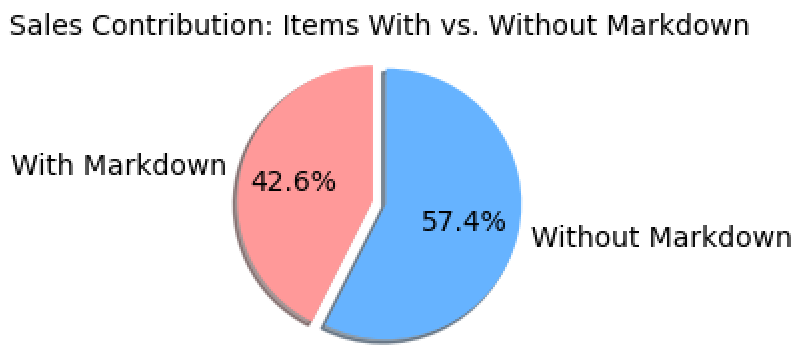
Out[12]:

	ID	Branded?	Buyer	Vendor	Cost	Initial Price	Markdown	Week Available	Week of Markdown	Sales by Week 3
0	1	1	1005	61	84.925	197.50	0.5	6	17.0	2
1	2	0	1011	83	144.375	460.00	NaN	46	NaN	5
2	3	1	1011	85	67.825	172.50	NaN	46	NaN	7
3	4	1	1011	85	63.575	172.50	NaN	41	NaN	5
4	5	1	1005	89	92.400	220.00	0.5	7	12.0	3
...	...	...	...	...	...	...	...	...	...	..
4075	4076	1	1002	10	34.375	62.45	0.5	24	15.0	54
4076	4077	1	1002	45	31.875	62.45	0.5	4	24.0	2650
4077	4078	0	1003	18	11.000	24.95	NaN	2	NaN	960
4078	4079	0	1003	18	11.000	24.95	NaN	10	NaN	1674
4079	4080	0	1003	50	18.750	49.95	NaN	32	NaN	935

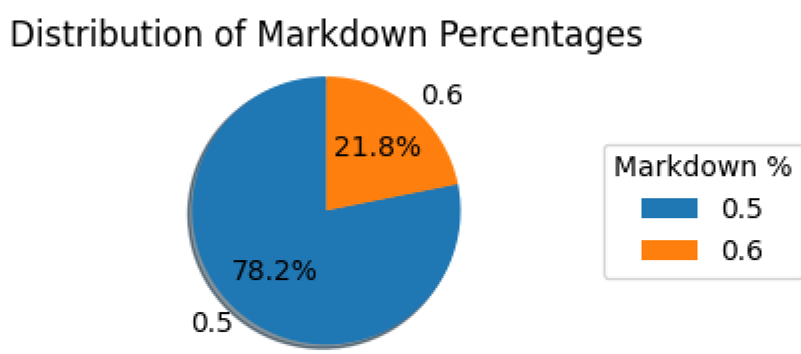
4080 rows × 22 columns

In [13]:

```
total_sales_sum = df['Sales Amount'].sum()
markdown_sales = df.groupby('Has_Markdown')['Sales Amount'].sum()
proportion_df = markdown_sales / total_sales_sum
sales_from_markdown_items = proportion_df['Has_Markdown' == False]
sales_with_markdown_pct = round(sales_from_markdown_items * 100, 2)
sales_without_markdown_pct = round((1 - sales_from_markdown_items) * 100, 2)

labels = ['With Markdown', 'Without Markdown']
sizes = [sales_with_markdown_pct, sales_without_markdown_pct]
colors = ['#ff9999', '#66b3ff']
explode = (0.1, 0)

plt.figure(figsize=(4, 2))
plt.pie(sizes, explode=explode, labels=labels, colors=colors,
        autopct='%1.1f%%', shadow=True, startangle=90)
plt.axis('equal')
plt.title('Sales Contribution: Items With vs. Without Markdown', fontsize=10)
plt.tight_layout()
plt.show()
```



In [14]:
```
markdown_counts = df['Markdown'].value_counts().sort_index()

plt.figure(figsize=(4, 2))
plt.pie(markdown_counts, labels=markdown_counts.index,autopct='%1.1f%%',
        startangle=90,shadow=True)
plt.axis('equal')
plt.title('Distribution of Markdown Percentages')
plt.legend(title='Markdown %', loc='center left', bbox_to_anchor=(1, 0, 0.5, 1
plt.tight_layout()
plt.show()
```



Correlation Analysis -

In [15]:
```
correlation_data = df[df['Markdown'].notna()].copy()
# Replacing 50 % Markdown with 0 and 60 % with 1 for better clustering
correlation_data['Markdown'] = correlation_data['Markdown'].replace({0.5: 0, 0
correlation_data = correlation_data.drop(columns=['ID', 'Buyer', 'Initial Pric
                                    'Units Left', 'Sunk Cost', 'Has_Markdown',
correlation_data
```

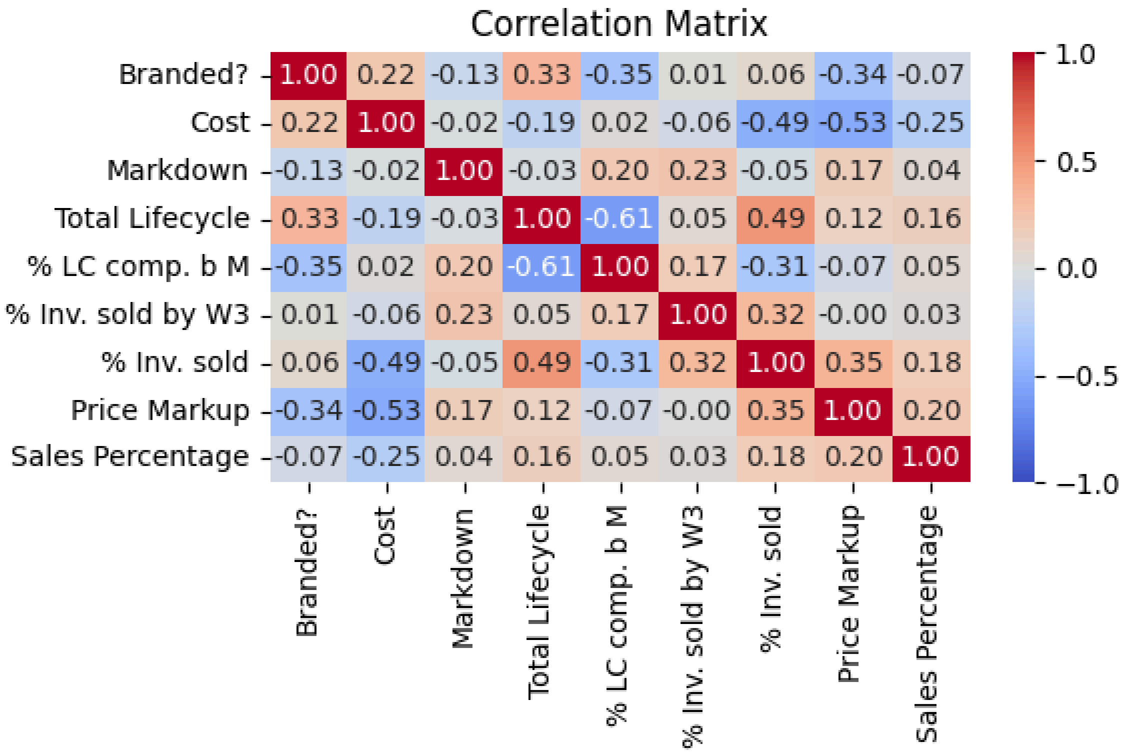
Out[15]:

	Branded?	Cost	Markdown	Total Lifecycle	% LC comp. b M	% Inv. sold by W3	% Inv. sold	Price Markup	Percer
0	1	84.925	0	26	0.653846	0.125000	0.750000	2.325581	0.0(
4	1	92.400	0	25	0.480000	0.150000	0.850000	2.380952	0.0(
13	0	72.000	0	9	0.666667	0.208333	0.750000	2.500000	0.0(
14	0	78.000	0	7	0.571429	0.375000	0.833333	2.500000	0.0(
27	1	60.000	0	22	0.590909	0.433333	0.933333	2.250000	0.0(
...	...	...	...	...	...	...	...	...	
4071	1	31.875	0	28	0.857143	0.363573	0.859583	1.959216	0.0(
4072	1	31.875	0	28	0.750000	0.096122	0.781529	1.959216	0.0(
4073	1	31.875	0	28	0.857143	0.362828	0.857619	1.959216	0.0(
4075	1	34.375	0	21	0.714286	0.007186	0.448570	1.816727	0.0(
4076	1	31.875	0	28	0.857143	0.324000	0.765864	1.959216	0.0(

2281 rows × 9 columns

In [16]:

```
correlation_matrix = correlation_data.corr()

def plot_correlation(matrix):
  plt.figure(figsize=(6, 4))
  sns.heatmap(matrix, annot=True, cmap='coolwarm', vmin=-1, vmax=1, fmt='.2f')
  plt.title('Correlation Matrix')
  plt.tight_layout()
  plt.show()

plot_correlation(matrix=correlation_matrix)
```



In [17]:
```
correlation_data
```

Out[17]:

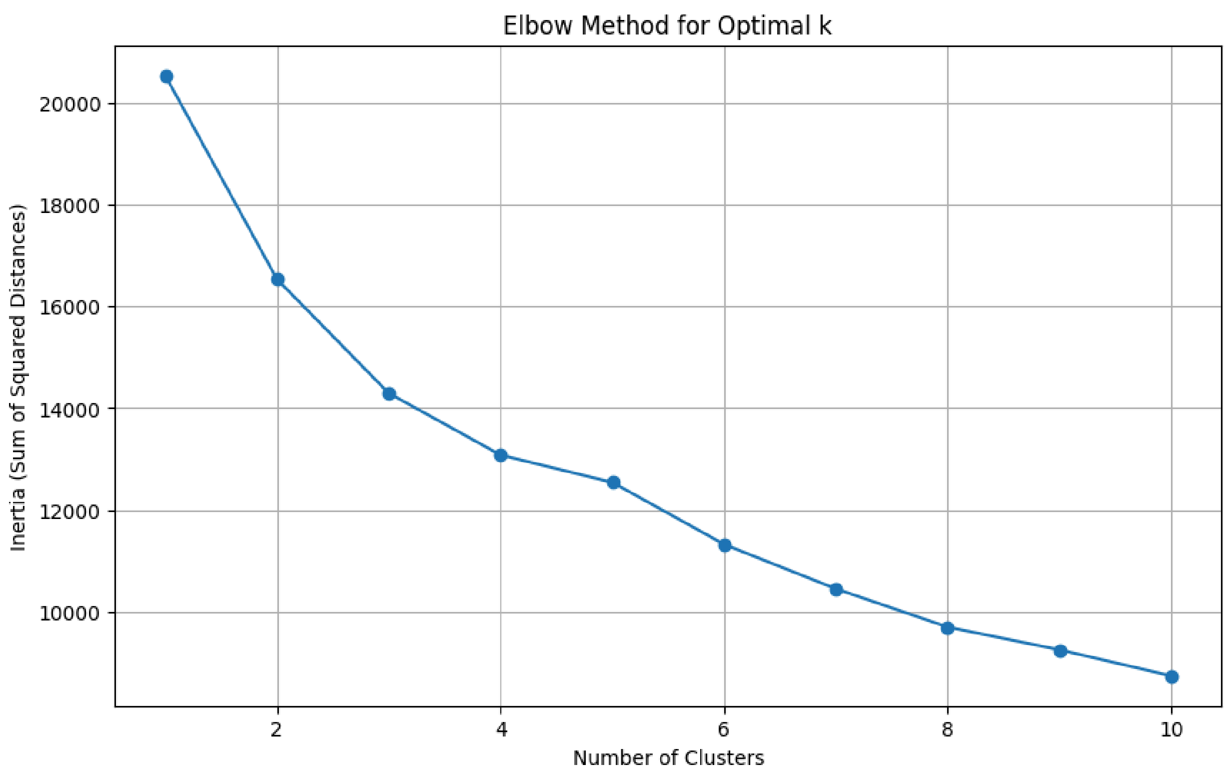
	Branded?	Cost	Markdown	Total Lifecycle	% LC comp. b M	% Inv. sold by W3	% Inv. sold	Price Markup	Percei
0	1	84.925	0	26	0.653846	0.125000	0.750000	2.325581	0.0(
4	1	92.400	0	25	0.480000	0.150000	0.850000	2.380952	0.0(
13	0	72.000	0	9	0.666667	0.208333	0.750000	2.500000	0.0(
14	0	78.000	0	7	0.571429	0.375000	0.833333	2.500000	0.0(
27	1	60.000	0	22	0.590909	0.433333	0.933333	2.250000	0.0(
...	...	...	...	...	...	...	...	...	
4071	1	31.875	0	28	0.857143	0.363573	0.859583	1.959216	0.0(
4072	1	31.875	0	28	0.750000	0.096122	0.781529	1.959216	0.0(
4073	1	31.875	0	28	0.857143	0.362828	0.857619	1.959216	0.0(
4075	1	34.375	0	21	0.714286	0.007186	0.448570	1.816727	0.0(
4076	1	31.875	0	28	0.857143	0.324000	0.765864	1.959216	0.0(

2281 rows × 9 columns

CLUSTERING -

In [18]:
```
numerical_cols = correlation_data.select_dtypes(include=['int64', 'float64']).c
data_for_clustering = correlation_data[numerical_cols].copy()
```

```
# Handling missing values (if any)
data_for_clustering = data_for_clustering.fillna(data_for_clustering.mean())

scaler = StandardScaler()
scaled_data = scaler.fit_transform(data_for_clustering)

# Running the Elbow Method chart - getting number of PCs
inertia = []
k_range = range(1, 11)
for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(scaled_data)
    inertia.append(kmeans.inertia_)

plt.figure(figsize=(10, 6))
plt.plot(k_range, inertia, 'o-')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia (Sum of Squared Distances)')
plt.title('Elbow Method for Optimal k')
plt.grid(True)
plt.show()
```

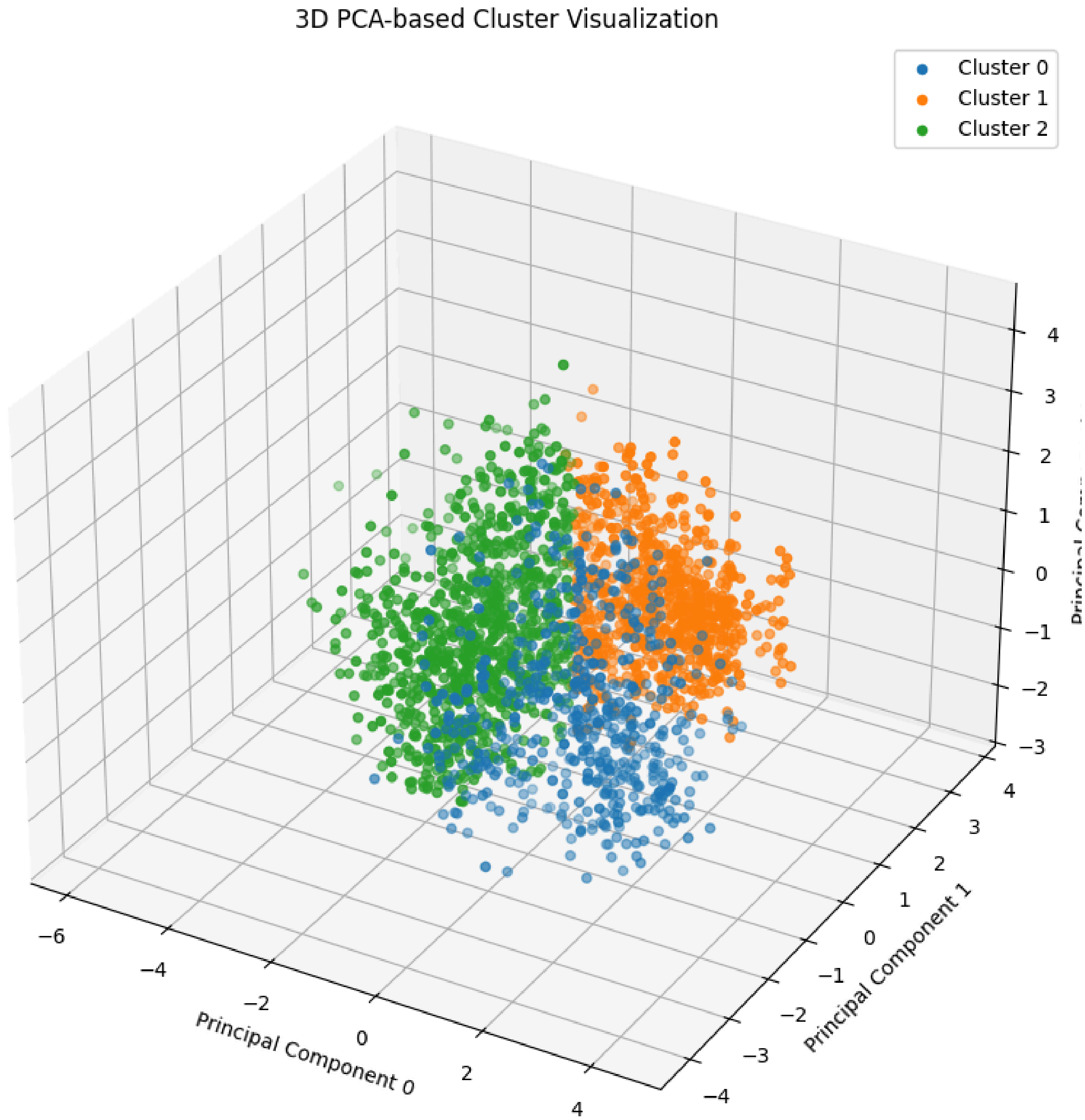


3 Clusters -

Principal Component Analysis with 3 components - **

In [19]:
```
optimal_k = 3
kmeans = KMeans(n_clusters=optimal_k)
cluster_labels = kmeans.fit_predict(scaled_data)

data_for_clustering['Cluster'] = cluster_labels
```

```
cluster_summary = data_for_clustering.groupby('Cluster').mean()
PC_components = ['PC0', 'PC1', 'PC2']

pca = PCA(n_components=3)
pca_result = pca.fit_transform(scaled_data)
pca_df = pd.DataFrame(data=pca_result, columns=PC_components)
pca_df['Cluster'] = cluster_labels
fig = plt.figure(figsize=(14, 10))
ax = fig.add_subplot(111, projection='3d')

for cluster in range(optimal_k):
    cluster_data = pca_df[pca_df['Cluster'] == cluster]
    ax.scatter(cluster_data['PC0'], cluster_data['PC1'], cluster_data['PC2'],

ax.set_title('3D PCA-based Cluster Visualization')
ax.set_xlabel('Principal Component 0')
ax.set_ylabel('Principal Component 1')
ax.set_zlabel('Principal Component 2')
ax.legend()
plt.show()
```

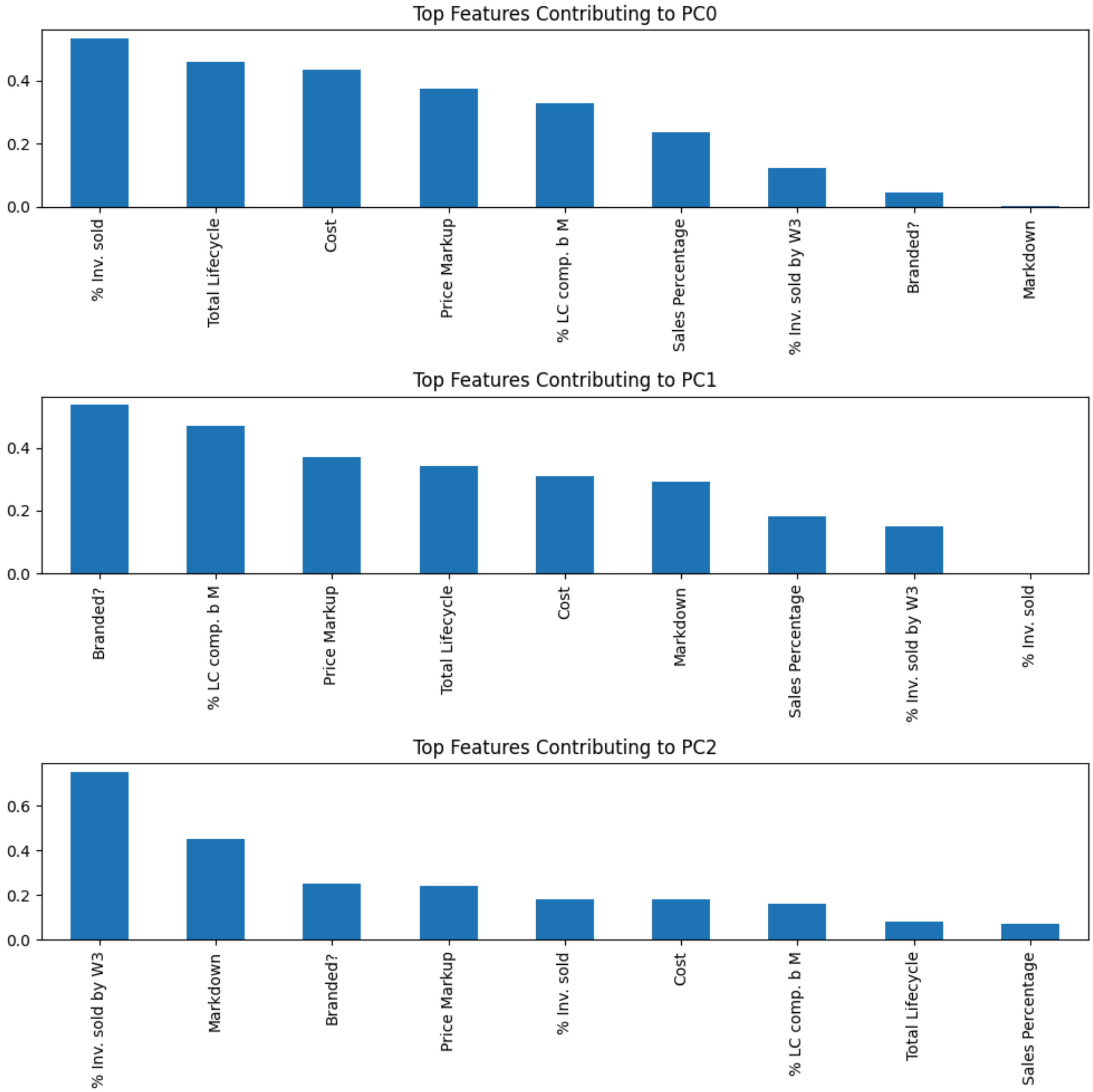


In [20]:
```
components = pca.components_
feature_names = correlation_data.columns
loadings = pd.DataFrame(components.T, index=feature_names, columns=PC_componen
print("PCA Component Loadings (contributions of each feature):")
print(loadings)
explained_variance = pca.explained_variance_ratio_
print("\nExplained Variance Ratio:")
for i, variance in enumerate(explained_variance):
    print(f"PC{i+1}: {variance:.4f} ({variance*100:.2f}%)")
print(f"Total Variance Explained: {sum(explained_variance)*100:.2f}%")
```

```
PCA Component Loadings (contributions of each feature):
                         PC0       PC1       PC2
Branded?            0.043331  0.537373  0.250868
Cost               -0.432085  0.310898  0.180600
Markdown           -0.001124 -0.291938  0.454132
Total Lifecycle     0.459741  0.341178  0.083609
% LC comp. b M     -0.326221 -0.469804  0.161279
% Inv. sold by W3   0.121564 -0.150273  0.754097
% Inv. sold         0.532995 -0.000903  0.182471
Price Markup        0.372321 -0.369960 -0.240255
Sales Percentage    0.236974 -0.181032 -0.074380

Explained Variance Ratio:
PC1: 0.2678 (26.78%)
PC2: 0.2198 (21.98%)
PC3: 0.1385 (13.85%)
Total Variance Explained: 62.61%
```

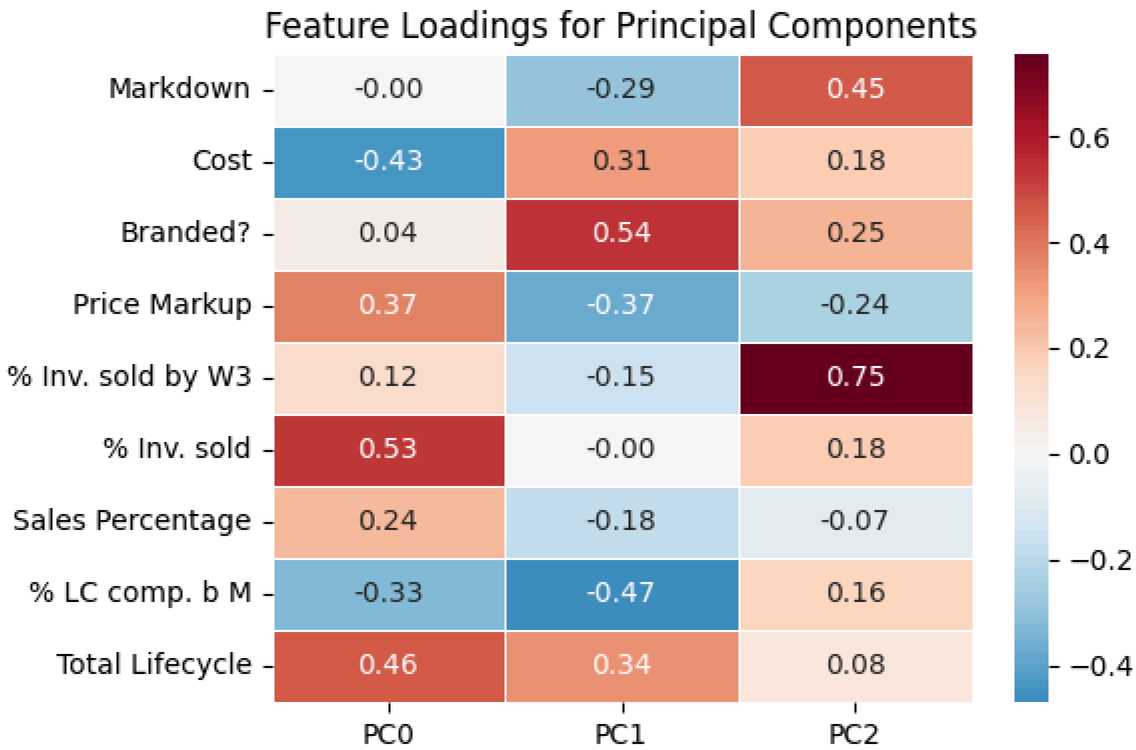
In [21]:

```python
plt.figure(figsize=(10, 10))
for i, pc in enumerate(PC_components):
    plt.subplot(3, 1, i+1)
    pc_loadings = loadings[pc].abs().sort_values(ascending=False)
    top_features = min(10, len(pc_loadings))
    pc_loadings[:top_features].plot(kind='bar')
    plt.title(f'Top Features Contributing to {pc}')
    plt.tight_layout()
plt.show()
```



In [22]:

```
all_important_features = set()
for pc in PC_components:
    pc_loadings = loadings[pc].abs().sort_values(ascending=False)
    top_features = min(10, len(pc_loadings))
    all_important_features.update(pc_loadings[:top_features].index)
all_important_features_list = list(all_important_features)
heatmap_data = loadings.loc[all_important_features_list, PC_components]
plt.figure(figsize=(6, 4))
sns.heatmap(heatmap_data, cmap='RdBu_r', center=0, annot=True, fmt='.2f', linew
plt.title('Feature Loadings for Principal Components')
plt.tight_layout()
plt.show()
```



Inventory Sold by Week 3 is an extremely important indicator for Cluster 2

Total inventory sold is an important indicator for Cluster 0

Most branded items show characterstics common for items in Cluster 1

Cluster 1 items are markdown after a large part of their lifecycle is completed.

Overall, there are several insights we can get from the heatmap above.

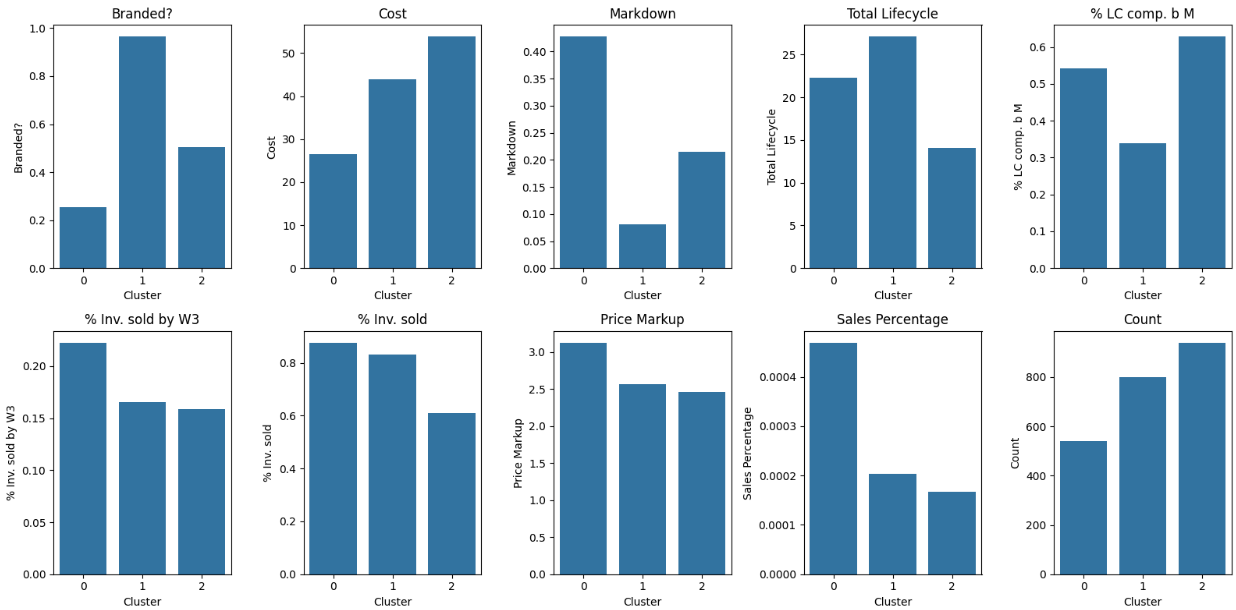
In [23]:
```
cluster_counts = data_for_clustering['Cluster'].value_counts().sort_index()
cluster_summary['Count'] = cluster_counts
cluster_summary
```

Out[23]:

Cluster	Branded?	Cost	Markdown	Total Lifecycle	% LC comp. b M	% Inv. sold by W3	% Inv. sold	Price Markup
0	0.255556	26.573287	0.427778	22.311111	0.542633	0.222641	0.876851	3.124399
1	0.965044	43.878059	0.081149	27.113608	0.338111	0.165753	0.832235	2.563636
2	0.504255	53.852181	0.214894	14.038298	0.628541	0.158829	0.610209	2.455600

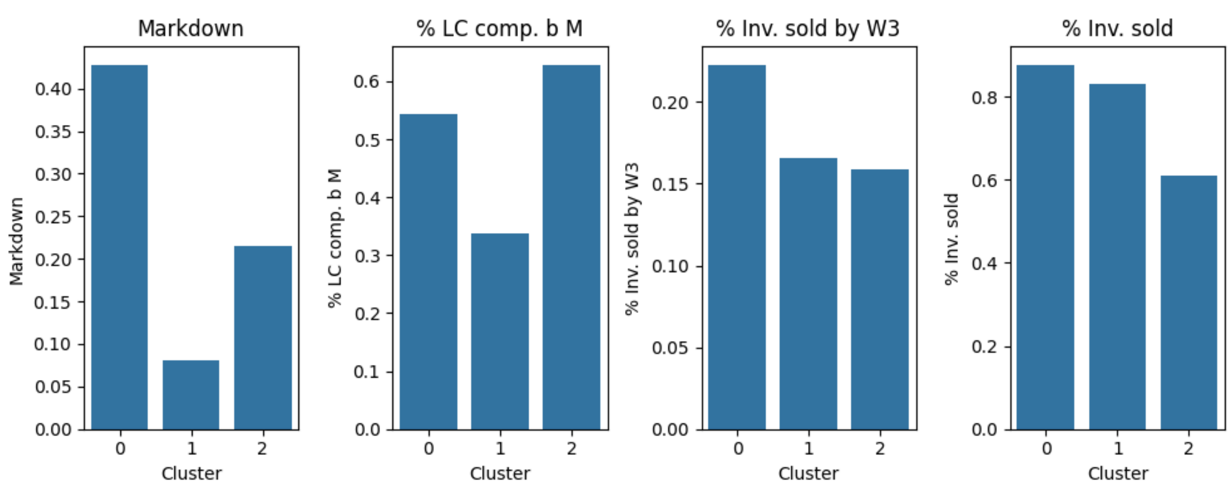
In [24]:
```
plt.figure(figsize=(16, 8))

for i, metric in enumerate(cluster_summary.columns):
    row = i // 5
    col = i % 5
    plt.subplot(2, 5, i+1)
    sns.barplot(x=cluster_summary.index, y=cluster_summary[metric])
```

```
    plt.title(f'{metric}')
    plt.ylabel(metric)
    plt.xlabel('Cluster')

plt.tight_layout()
plt.show()
```



In [25]:

```
report_metrics = ['Markdown', '% LC comp. b M', '% Inv. sold by W3', '% Inv. s

plt.figure(figsize=(10, 4))

for i, metric in enumerate(report_metrics):
    row = i // 4
    col = i % 4
    plt.subplot(1, 4, i+1)
    sns.barplot(x=cluster_summary.index, y=cluster_summary[metric])
    plt.title(f'{metric}')
    plt.ylabel(metric)
    plt.xlabel('Cluster')

plt.tight_layout()
plt.show()
```



Analysis of Cluster Characterstics -

Cluster 0 - Higher Markdowns - 65-70%, Earlier in Product Lifecycle

- Incoming revenue from items in this cluster is lower.
- Cost of items in this cluster is relatively high and average product lifecycle is relatively low.
- The inventory sold in the end is low.
- Inventory sold by Week 3 is also relatively lower for this cluster.
- **We need items in this cluster to move faster.**
- Most items (800+) belong to this cluster.
- Initial price markup is also lower for these items but its still on average 2 times cost. We should reduce initial price or definitely have higher and earlier markdowns.

Cluster 1 - Same 50%/60% markdowns but definitely later in Product Lifecycle

- Incoming revenue is similar to Cluster 0, very low compared to Cluster 2.
- About 80% inventory is sold at the end.
- Only about 15% inventory is sold by W3.
- About 70% of product lifecycle is still left after markdown.
- Thus, we can conclude that markdowns are effective since inventory sells out but we should delay the markdowns from 30% to 50% of the product lifecycle. This would help us maximize our revenue.
- The average lifecycle is also the longest for this cluster and we would have time after markdown for more sales.

Cluster 2 - Lower Markdowns - 30-40%, Later in in Product Lifecycle

- Incoming revenue is from this cluster is really high compared to others. We can maximize it further.
- 80%+ inventory is sold at the end.
- 20%+ inventory is sold by W3.
- About 45% of product lifecycle is still left after markdown.
- Thus, we can conclude that markdowns are effective since inventory sells out fast but we should reduce the markdowns to 30-40% instead of 50/60% and delay the markdowns from 50% to 60% of the product lifecycle. This would help us maximize our revenue.
- The average lifecycle is about 22 weeks which is high and we would have about 10 weeks after markdown for high sales.

REGRESSION -

In [26]:
```
data_for_regression = data_for_clustering[['Branded?', 'Cost', 'Price Markup',
data_for_regression
```

Out[26]:

	Branded?	Cost	Price Markup	Total Lifecycle	% Inv. sold by W3	Cluster
0	1	84.925	2.325581	26	0.125000	2
4	1	92.400	2.380952	25	0.150000	1
13	0	72.000	2.500000	9	0.208333	2
14	0	78.000	2.500000	7	0.375000	2
27	1	60.000	2.250000	22	0.433333	1
...	...	...	...	...	...	...
4071	1	31.875	1.959216	28	0.363573	0
4072	1	31.875	1.959216	28	0.096122	0
4073	1	31.875	1.959216	28	0.362828	0
4075	1	34.375	1.816727	21	0.007186	2
4076	1	31.875	1.959216	28	0.324000	0

2281 rows × 6 columns

In [27]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_s

X = data_for_regression[['Branded?', 'Cost', 'Price Markup', 'Total Lifecycle'
y = data_for_regression['Cluster']

X_temp, X_test, y_temp, y_test = train_test_split(X, y, test_size=0.2)
X_train, X_val, y_train, y_val = train_test_split(X_temp, y_temp, test_size=0.

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_val_scaled = scaler.transform(X_val)
X_test_scaled = scaler.transform(X_test)

model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train_scaled, y_train)

y_val_pred = model.predict(X_val_scaled)
print("Validation Accuracy:", accuracy_score(y_val, y_val_pred))

y_test_pred = model.predict(X_test_scaled)
print("\n--- Final Test Results ---")
print("Test Accuracy:", accuracy_score(y_test, y_test_pred))
print("\nTest Classification Report:")
print(classification_report(y_test, y_test_pred))

feature_importance = pd.DataFrame({
```

```
    'Feature': X.columns,
    'Importance': model.feature_importances_
}).sort_values(by='Importance', ascending=False)

print("\nFeature Importance:")
print(feature_importance)
```

```
Validation Accuracy: 0.8728070175438597

--- Final Test Results ---
Test Accuracy: 0.8818380743982495

Test Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.82      0.84       103
           1       0.86      0.89      0.87       163
           2       0.91      0.91      0.91       191

    accuracy                           0.88       457
   macro avg       0.88      0.87      0.87       457
weighted avg       0.88      0.88      0.88       457


Feature Importance:
             Feature  Importance
3    Total Lifecycle    0.363566
2       Price Markup    0.231902
1               Cost    0.169801
4  % Inv. sold by W3    0.124331
0           Branded?    0.110401
```

Cluster Predictions with Probabilities for Items not Markdown -

In [28]:

```
non_markdown = df.loc[df['Has_Markdown'] == False][['Branded?', 'Cost', 'Price
X_non_markdown_scaled = scaler.transform(non_markdown)
non_markdown_predictions = model.predict(X_non_markdown_scaled)

non_markdown['Predicted_Cluster'] = non_markdown_predictions
prediction_probabilities = model.predict_proba(X_non_markdown_scaled)

for i, cluster in enumerate(model.classes_):
    non_markdown[f'Prob_Cluster_{cluster}'] = prediction_probabilities[:, i]

print("\nPrediction distribution:")
print(non_markdown['Predicted_Cluster'].value_counts(normalize=True))
non_markdown
```

```
Prediction distribution:
Predicted_Cluster
2    0.657588
0    0.184547
1    0.157865
Name: proportion, dtype: float64
```

Out[28]:

	Branded?	Cost	Price Markup	Total Lifecycle	% Inv. sold by W3	Predicted_Cluster	Prob_Cluster_0	Pr
1	0	144.375	3.186147	8	0.312500	2	0.35	
2	1	67.825	2.543310	8	0.388889	2	0.00	
3	1	63.575	2.713331	8	0.277778	2	0.02	
5	1	66.250	2.566038	28	0.100000	1	0.01	
6	1	90.000	2.194444	16	0.000000	2	0.00	
...	...	...	...	...	...	...	...	
4068	0	11.000	2.268182	26	0.116014	0	0.85	
4074	0	11.000	2.268182	8	0.246008	2	0.12	
4077	0	11.000	2.268182	26	0.109265	0	0.82	
4078	0	11.000	2.268182	18	0.129999	2	0.01	
4079	0	18.750	2.664000	9	0.070769	2	0.16	

1799 rows × 9 columns