Customer Segmentation

This notebook runs the full segmentation pipeline: loading the data (uses the `market` sheet), feature engineering, clustering (KMeans), evaluation and visualizations. It also summarizes findings and actionable recommendations so you can export or present results directly from the notebook.

Assumptions:

- The repository contains `data_processing.py`, `features.py`, and `pipeline.py` which this notebook may import.
- Data source: `Supermarket Data.xlsx` downloaded from the Kaggle dataset into a cache; `data_processing.load_raw()` will prefer the `market` sheet.

In [1]:

```python
# 1) Imports and environment
import sys
from pathlib import Path
repo_root = Path('..').resolve()
if str(repo_root) not in sys.path:
    sys.path.insert(0, str(repo_root))

# Ensure we can import packages from the managed virtual environment (.venv)
venv_site_packages = repo_root / '.venv' / 'Lib' / 'site-packages'
if venv_site_packages.exists() and str(venv_site_packages) not in sys.path:
    sys.path.insert(0, str(venv_site_packages))

print('Added repo root to sys.path:', repo_root)
if venv_site_packages.exists():
    print('Added .venv site-packages to sys.path:', venv_site_packages)

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import joblib

# scikit-learn
from sklearn.preprocessing import StandardScaler
```

```python
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

# Helpers from this repo
from data_processing import load_raw
from features import build_transaction_features, build_store_aggregates

# Plot settings
%matplotlib inline
sns.set(style='whitegrid')

print('Notebook running with pandas', pd.__version__)
```

```
Added repo root to sys.path: C:\Users\jeff\Projects\deep-learning\customer_segmentation
Notebook running with pandas 2.3.3
```

In [2]:

```python
# 2) Load data

# load_raw prefers the `market` sheet and handles column normalization
raw_df = load_raw()
print('Loaded dataframe shape:', raw_df.shape)
raw_df.head()
```

```
C:\Users\jeff\Projects\deep-learning\customer_segmentation\data_processing.py:70: UserWarning: Could not infer forma
t, so each element will be parsed individually, falling back to `dateutil`. To ensure parsing is consistent and as-ex
pected, please specify a format.
  df['datetime'] = pd.to_datetime(df['date'].astype(str) + ' ' + df['time'].astype(str), errors='coerce')
Loaded dataframe shape: (1464, 33)
```

Out[2]:

	supermarket	no_of_items	variation	total	paid	change	type	food	snack	beverage	...	24hr	day_1	month	year	hc
0	acacia	1	1	90.0	100	10.0	cash	yes	no	no	...	no	20	5	2017.0	
1	acacia	1	1	90.0	500	410.0	cash	yes	no	no	...	no	20	5	2017.0	
2	acacia	3	1	270.0	300	30.0	cash	yes	no	no	...	no	20	5	2017.0	
3	acacia	3	1	137.0	200	63.0	cash	yes	no	no	...	no	20	5	2017.0	
4	acacia	1	1	75.0	80	5.0	cash	yes	no	no	...	no	20	5	2017.0	

5 rows × 33 columns

In [3]:

```
# 3) Quick inspection
print('Columns:', raw_df.columns.tolist())
print('\nMissing value counts (top 20):')
print(raw_df.isnull().sum().sort_values(ascending=False).head(20))

# Basic value counts for key categorical fields (if present)
for c in ['supermarket','payment_type','category']:
    if c in raw_df.columns:
        print(f"\nValue counts for {c} (top 10):")
        print(raw_df[c].value_counts().head(10))
```

```
Columns: ['supermarket', 'no_of_items', 'variation', 'total', 'paid', 'change', 'type', 'food', 'snack', 'beverage', 'consumables', 'high_end', 'asset', 'fixed_asset', 'date', 'mall', 'time', 'time_type', 'type_market', 'location', 'loc_category', 'day', 'day_type', '24hr', 'day_1', 'month', 'year', 'hour', 'item_no_cat', 'total_cat', 'paid_cat', 'change_cat', 'datetime']

Missing value counts (top 20):
datetime       3
year           2
supermarket    1
no_of_items    0
variation      0
change         0
type           0
total          0
paid           0
beverage       0
consumables    0
high_end       0
asset          0
fixed_asset    0
date           0
food           0
snack          0
time           0
mall           0
time_type      0
dtype: int64

Value counts for supermarket (top 10):
supermarket
karrymart     520
tumaini       268
nakumatt      180
cleanshelf    128
tuskys        126
ukwala         56
acacia         53
naivas         30
eastmatt       26
Tuskys         16
Name: count, dtype: int64
```

In [4]:
```python
# 4) Feature engineering

features = build_transaction_features(raw_df)
print('Features shape:', features.shape)
features.head()
```

```
Features shape: (1464, 13)
```

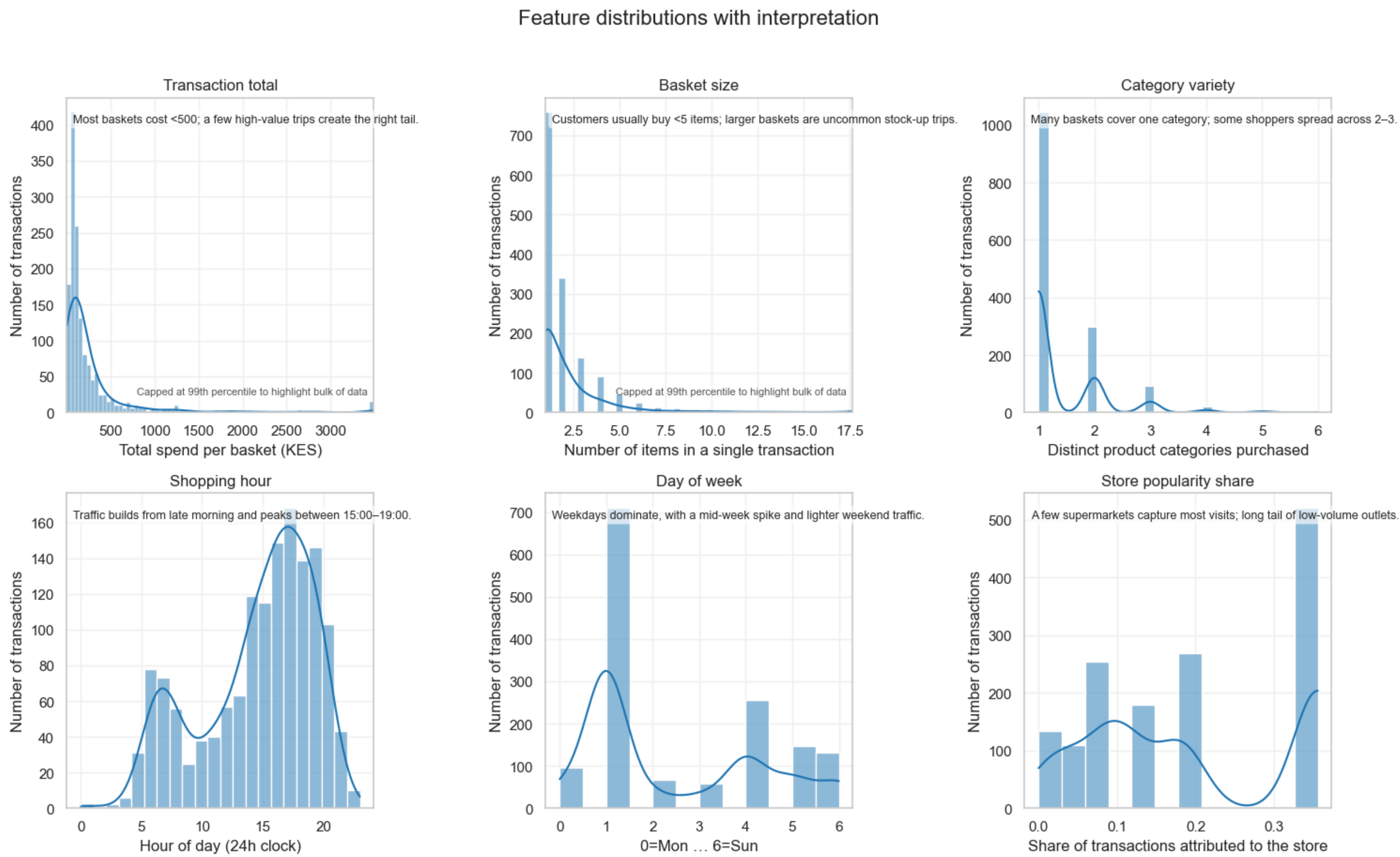
Out[4]:

	no_of_items	variation	total	paid	change	hour	dayofweek	is_weekend	month	supermarket_freq	is_cash	is_card	is_mp
0	1	1	90.0	100	10.0	19.0	5.0	1	5.0	0.036202	1	0	
1	1	1	90.0	500	410.0	19.0	5.0	1	5.0	0.036202	1	0	
2	3	1	270.0	300	30.0	19.0	5.0	1	5.0	0.036202	1	0	
3	3	1	137.0	200	63.0	19.0	5.0	1	5.0	0.036202	1	0	
4	1	1	75.0	80	5.0	18.0	5.0	1	5.0	0.036202	1	0	

In [5]:
```python
# 4b) Quick feature distributions with contextual notes
feature_cfg = {
    'total': {
        'title': 'Transaction total',
        'xlabel': 'Total spend per basket (KES)',
        'note': 'Most baskets cost <500; a few high-value trips create the right tail.',
        'clip_quantile': 0.99
    },
    'no_of_items': {
        'title': 'Basket size',
        'xlabel': 'Number of items in a single transaction',
        'note': 'Customers usually buy <5 items; larger baskets are uncommon stock-up trips.',
        'clip_quantile': 0.995
    },
    'variation': {
        'title': 'Category variety',
        'xlabel': 'Distinct product categories purchased',
        'note': 'Many baskets cover one category; some shoppers spread across 2-3.'
    },
    'hour': {
        'title': 'Shopping hour',
```

```python
        'xlabel': 'Hour of day (24h clock)',
        'note': 'Traffic builds from late morning and peaks between 15:00–19:00.'
    },
    'dayofweek': {
        'title': 'Day of week',
        'xlabel': '0=Mon … 6=Sun',
        'note': 'Weekdays dominate, with a mid-week spike and lighter weekend traffic.'
    },
    'supermarket_freq': {
        'title': 'Store popularity share',
        'xlabel': 'Share of transactions attributed to the store',
        'note': 'A few supermarkets capture most visits; long tail of low-volume outlets.'
    }
}

fig_dist, axs = plt.subplots(2, 3, figsize=(15, 9))
axs = axs.flatten()
for ax, (col, cfg) in zip(axs, feature_cfg.items()):
    if col not in features.columns:
        ax.set_visible(False)
        continue

    series = features[col].dropna()
    clip_q = cfg.get('clip_quantile')
    if clip_q:
        upper = series.quantile(clip_q)
        series = series.clip(upper=upper)
        ax.set_xlim(series.min(), upper)
        ax.text(
            0.98,
            0.05,
            f'Capped at {int(clip_q*100)}th percentile to highlight bulk of data',
            transform=ax.transAxes,
            fontsize=8,
            va='bottom',
            ha='right',
            color='#555555'
        )

    sns.histplot(x=series, ax=ax, kde=True, color='#1f77b4')
    ax.set_title(cfg['title'])
    ax.set_xlabel(cfg['xlabel'])
```

```python
    ax.set_ylabel('Number of transactions')
    ax.grid(alpha=0.2)
    ax.text(
        0.02,
        0.95,
        cfg['note'],
        transform=ax.transAxes,
        fontsize=9,
        va='top',
        ha='left',
        bbox=dict(boxstyle='round,pad=0.3', facecolor='white', alpha=0.65, edgecolor='none')
    )

fig_dist.suptitle('Feature distributions with interpretation', fontsize=16, y=1.02)
plt.tight_layout()
```

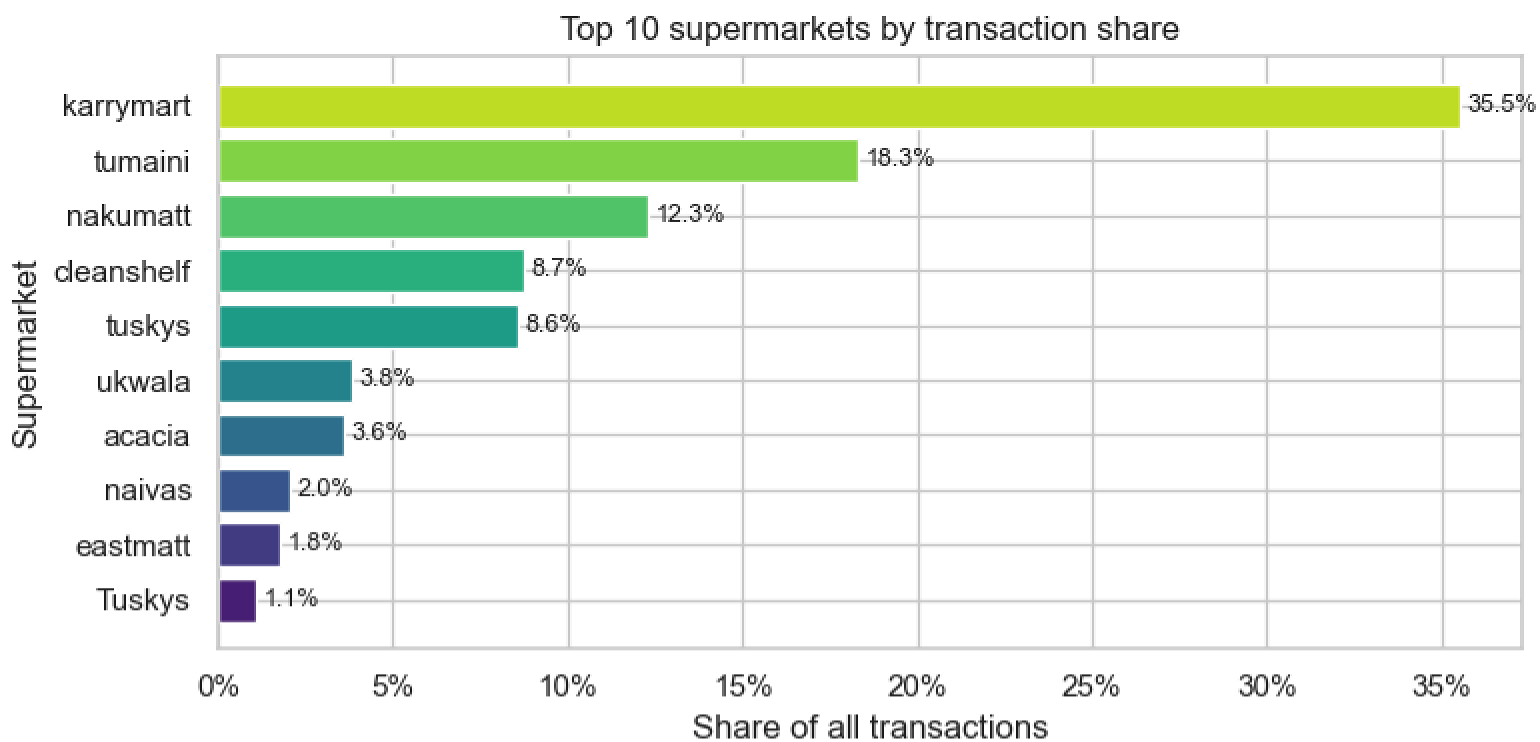


In [6]:

```python
# 4c) Store popularity (top 10 supermarkets by transaction share)
from matplotlib.ticker import FuncFormatter

store_counts = raw_df['supermarket'].fillna('UNKNOWN').value_counts()
store_summary = (
    pd.DataFrame({
        'supermarket': store_counts.index,
        'transactions': store_counts.values
    })
)
```

```
store_summary['share'] = store_summary['transactions'] / store_summary['transactions'].sum()

print('Top stores by transaction count:')
store_summary.head(10)

fig_store_pop, ax_store_pop = plt.subplots(figsize=(8, 4))
subset = store_summary.head(10)
ax_store_pop.barh(subset['supermarket'][::-1], subset['share'][::-1], color=sns.color_palette('viridis', len(subset))
ax_store_pop.set_title('Top 10 supermarkets by transaction share')
ax_store_pop.set_xlabel('Share of all transactions')
ax_store_pop.set_ylabel('Supermarket')
ax_store_pop.xaxis.set_major_formatter(FuncFormatter(lambda val, pos: f"{val:.0%}"))
for idx, (y, share) in enumerate(zip(subset['supermarket'][::-1], subset['share'][::-1])):
    ax_store_pop.text(share + 0.002, idx, f"{share:.1%}", va='center', ha='left', fontsize=9)
plt.tight_layout()
```

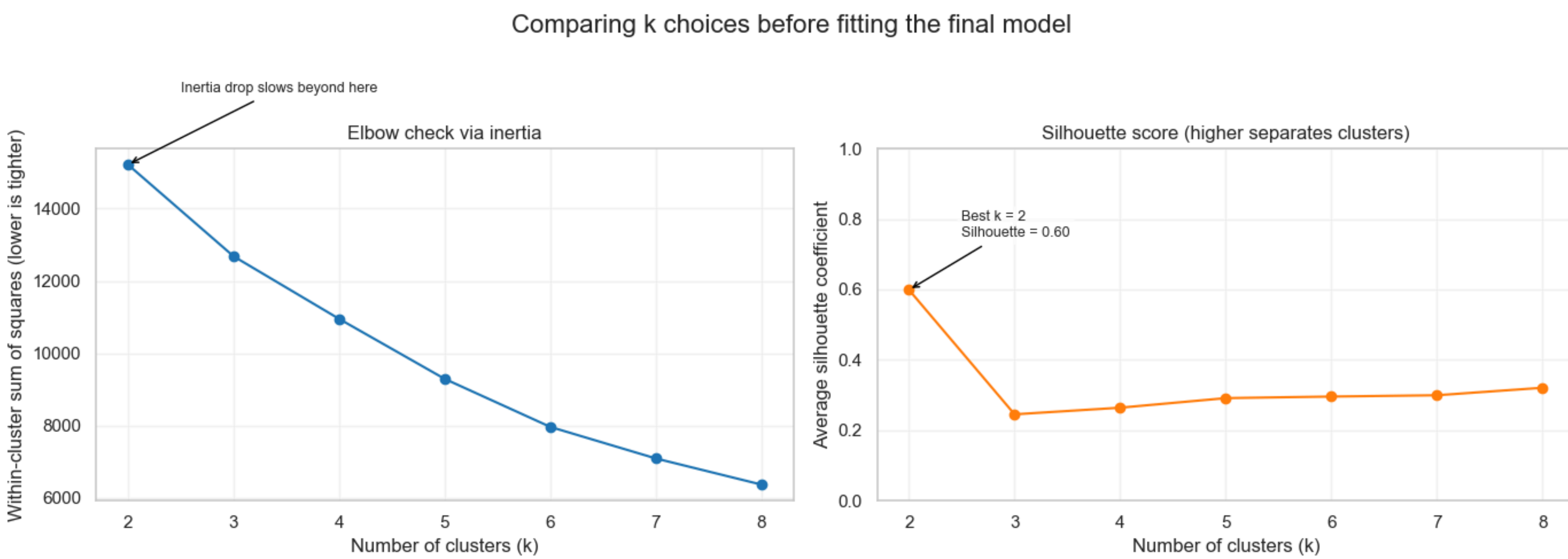
```
Top stores by transaction count:
```



In [7]:
```python
# 5) Scale features and evaluate candidate cluster counts
scaler = StandardScaler()
X = scaler.fit_transform(features)

ks = range(2, 9)
scores = {}
inertias = {}
for k in ks:
    km = KMeans(n_clusters=k, random_state=42, n_init=20)
    labels = km.fit_predict(X)
    try:
        s = silhouette_score(X, labels)
    except Exception:
        s = float('nan')
    scores[k] = s
    inertias[k] = km.inertia_
    print(f'k={k}: silhouette={s:.4f}, inertia={km.inertia_:.2f}')

best_k = max(scores, key=lambda kk: scores[kk] if not pd.isna(scores[kk]) else -1)

fig_eval, axes = plt.subplots(1, 2, figsize=(14, 5))

# Inertia (Elbow) plot
axes[0].plot(list(inertias.keys()), list(inertias.values()), marker='o', color='#1f77b4')
axes[0].set_title('Elbow check via inertia')
axes[0].set_xlabel('Number of clusters (k)')
axes[0].set_ylabel('Within-cluster sum of squares (lower is tighter)')
axes[0].grid(alpha=0.2)
axes[0].annotate(
    'Inertia drop slows beyond here',
    xy=(best_k, inertias[best_k]),
    xytext=(best_k + 0.5, inertias[best_k] + 2000),
    arrowprops=dict(arrowstyle='->', color='black'),
    fontsize=9,
    bbox=dict(boxstyle='round,pad=0.3', facecolor='white', alpha=0.7, edgecolor='none')
)

# Silhouette plot
axes[1].plot(list(scores.keys()), [scores[k] for k in scores], marker='o', color='#ff7f0e')
axes[1].set_title('Silhouette score (higher separates clusters)')
axes[1].set_xlabel('Number of clusters (k)')
```

```
axes[1].set_ylabel('Average silhouette coefficient')
axes[1].set_ylim(0, 1)
axes[1].grid(alpha=0.2)
axes[1].annotate(
    f'Best k = {best_k}\nSilhouette = {scores[best_k]:.2f}',
    xy=(best_k, scores[best_k]),
    xytext=(best_k + 0.5, min(scores[best_k] + 0.15, 0.95)),
    arrowprops=dict(arrowstyle='->', color='black'),
    fontsize=9,
    bbox=dict(boxstyle='round,pad=0.3', facecolor='white', alpha=0.7, edgecolor='none')
)

fig_eval.suptitle('Comparing k choices before fitting the final model', fontsize=16)
plt.tight_layout()
```

```
k=2: silhouette=0.5988, inertia=15213.14
k=3: silhouette=0.2452, inertia=12680.09
k=4: silhouette=0.2640, inertia=10950.24
k=5: silhouette=0.2912, inertia=9292.62
k=6: silhouette=0.2957, inertia=7966.07
k=7: silhouette=0.2993, inertia=7094.07
k=8: silhouette=0.3206, inertia=6372.29
```



In [8]:
```python
# 6) Fit final model with best k and inspect clusters
best_k = max(scores, key=lambda kk: scores[kk] if not pd.isna(scores[kk]) else -1)
print('Best k by silhouette:', best_k, 'score=', scores[best_k])

km_final = KMeans(n_clusters=best_k, random_state=42, n_init=20)
labels = km_final.fit_predict(X)
raw_df['cluster'] = labels
features['cluster'] = labels

cluster_sizes = raw_df['cluster'].value_counts().sort_index()
print('\nCluster sizes:\n', cluster_sizes)

cluster_profiles = features.groupby('cluster').mean()
cluster_profiles
```

```
Best k by silhouette: 2 score= 0.5987584373803047

Cluster sizes:
 cluster
0    1379
1      85
Name: count, dtype: int64
```

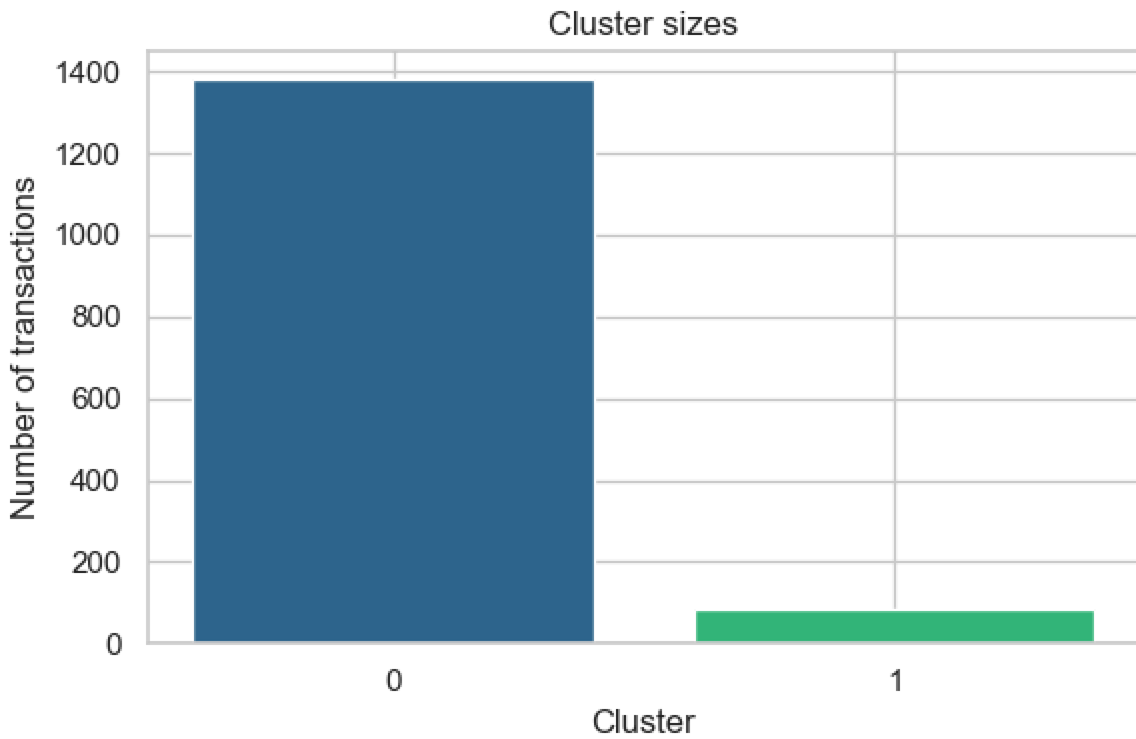
Out[8]:

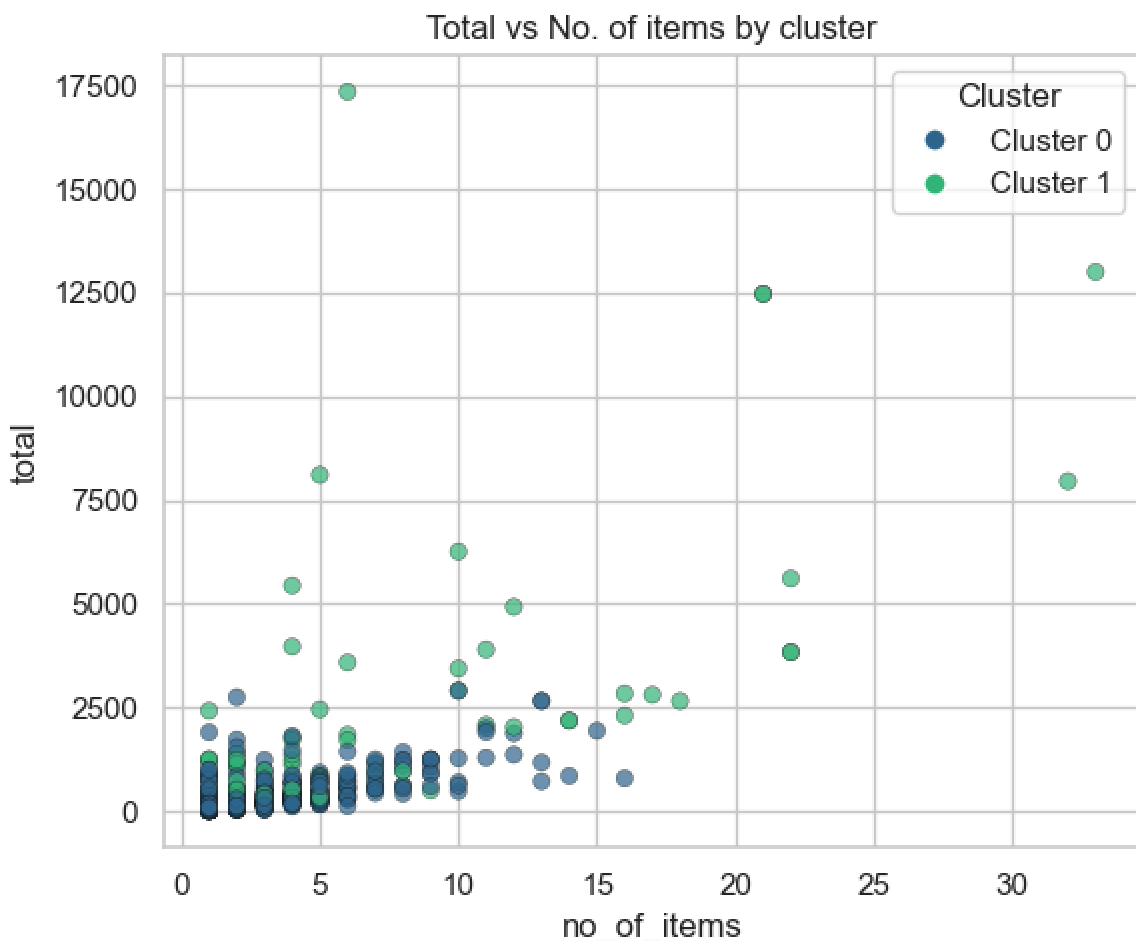
cluster	no_of_items	variation	total	paid	change	hour	dayofweek	is_weekend	month	supermarket
0	2.037708	1.337926	198.569181	364.714286	173.142589	14.405366	2.408267	0.182741	6.168963	0.19
1	6.705882	2.376471	2148.478941	2165.223529	16.317647	16.341176	2.764706	0.294118	6.964706	0.1

In [9]:
```python
# 6b) Visual summaries
# Ensure output folder exists for any figures
from matplotlib.lines import Line2D
out = Path('..') / 'analysis_output'
out.mkdir(parents=True, exist_ok=True)

# Cluster size bar chart (use matplotlib directly to stay backend-agnostic)
fig_cluster, ax_cluster = plt.subplots(figsize=(6, 4))
ax_cluster.bar(cluster_sizes.index.astype(str), cluster_sizes.values, color=sns.color_palette('viridis', len(cluster_
ax_cluster.set_title('Cluster sizes')
```

```
ax_cluster.set_xlabel('Cluster')
ax_cluster.set_ylabel('Number of transactions')
plt.tight_layout()

# Scatter of total vs no_of_items coloured by cluster without relying on pandas plotting
fig_scatter = None
if {'total', 'no_of_items', 'cluster'}.issubset(features.columns):
    palette = sns.color_palette('viridis', len(cluster_sizes))
    colour_lookup = {cluster: palette[idx] for idx, cluster in enumerate(cluster_sizes.index)}
    colours = features['cluster'].map(colour_lookup)

    fig_scatter, ax_scatter = plt.subplots(figsize=(6, 5))
    ax_scatter.scatter(features['no_of_items'], features['total'], c=colours, alpha=0.7, edgecolor='k', linewidth=0.3
    ax_scatter.set_title('Total vs No. of items by cluster')
    ax_scatter.set_xlabel('no_of_items')
    ax_scatter.set_ylabel('total')
    handles = [Line2D([0], [0], marker='o', color='w', markerfacecolor=colour_lookup[c], markersize=8, label=f'Cluste
    ax_scatter.legend(handles=handles, title='Cluster')
    plt.tight_layout()

print('Generated additional cluster charts')
```

```
Generated additional cluster charts
```


Cluster sizes
Number of transactions
1400
1200
1000
800
600
400
200
0
0
1
Cluster



In [10]:

```
# 7) Save outputs
out = Path('..') / 'analysis_output'
out.mkdir(parents=True, exist_ok=True)

# save labeled transactions and cluster summaries
raw_df.to_csv(out / 'transactions_with_cluster_from_notebook.csv', index=False)
cluster_profiles.to_csv(out / 'cluster_profiles_mean_from_notebook.csv')
cluster_sizes.to_csv(out / 'cluster_sizes_from_notebook.csv')

# save model and scaler
joblib.dump(km_final, out / 'kmeans_model_from_notebook.joblib')
joblib.dump(scaler, out / 'scaler_from_notebook.joblib')
```

```python
# persist figures if they exist
# matplotlib.pyplot.Figure.savefig expects a str or file-like; convert Path -> str to satisfy type-checkers
if 'fig_dist' in globals():
    fig_dist.savefig(str(out / 'feature_distributions.png'), dpi=150, bbox_inches='tight')
if 'fig_eval' in globals():
    fig_eval.savefig(str(out / 'k_selection_diagnostics.png'), dpi=150, bbox_inches='tight')
if 'fig_cluster' in globals():
    fig_cluster.savefig(str(out / 'cluster_sizes_bar.png'), dpi=150, bbox_inches='tight')
if 'fig_scatter' in globals() and fig_scatter is not None:
    fig_scatter.savefig(str(out / 'cluster_scatter_total_items.png'), dpi=150, bbox_inches='tight')
if 'fig_store_pop' in globals():
    fig_store_pop.savefig(str(out / 'store_popularity_top10.png'), dpi=150, bbox_inches='tight')

print('Saved outputs to', out)
```

```
Saved outputs to ..\analysis_output
```

In [11]:

```python
# 8) Small cluster inspection and export
out = Path('..') / 'analysis_output'
out.mkdir(parents=True, exist_ok=True)

small_cluster_id = cluster_sizes.idxmin()
small_rows = raw_df[raw_df['cluster'] == small_cluster_id]
print(f'Smallest cluster is {small_cluster_id} with {len(small_rows)} rows')

display(small_rows.head())
summary = small_rows.describe(include='all')
if hasattr(summary.index, 'infer_objects'):
    summary.index = summary.index.infer_objects()
display(summary)

small_rows.to_csv(out / 'cluster_small_rows.csv', index=False)
print('Saved smallest cluster rows to', out)
```

```
Smallest cluster is 1 with 85 rows
```

	supermarket	no_of_items	variation	total	paid	change	type	food	snack	beverage	...	day_1	month	year	hou
5	nakumatt	22	3	5611.0	5611	0.0	card	yes	no	no	...	24	12	2016.0	16
7	chandarana	32	3	7955.0	7955	0.0	mpesa	yes	no	no	...	3	1	2017.0	19
10	tuskys	33	6	13005.0	13001	0.0	card	yes	no	no	...	7	12	2016.0	8
14	nakumatt	1	1	2420.0	2460	0.0	card	no	no	no	...	11	11	2016.0	8
15	nakumatt	12	2	4926.0	4926	0.0	card	yes	no	no	...	11	11	2016.0	8

5 rows × 34 columns

```
C:\Users\jeff\AppData\Local\Temp\ipykernel_10068\2477773834.py:10: FutureWarning: The behavior of value_counts with o
bject-dtype is deprecated. In a future version, this will *not* perform dtype inference on the resulting index. To re
tain the old behavior, use `result.index = result.index.infer_objects()`
  summary = small_rows.describe(include='all')
```

	supermarket	no_of_items	variation	total	paid	change	type	food	snack	beverage	...	day_1
count	85	85.000000	85.000000	85.000000	85.000000	85.000000	85	85	85	85	...	85.0
unique	9	NaN	NaN	NaN	NaN	NaN	4	2	2	2	...	25.0
top	nakumatt	NaN	NaN	NaN	NaN	NaN	mpesa	yes	no	no	...	26.0
freq	37	NaN	NaN	NaN	NaN	NaN	52	56	52	49	...	12.0
mean	NaN	6.705882	2.376471	2148.478941	2165.223529	16.317647	NaN	NaN	NaN	NaN	...	NaN
min	NaN	1.000000	1.000000	98.000000	98.000000	0.000000	NaN	NaN	NaN	NaN	...	NaN
25%	NaN	2.000000	1.000000	424.000000	424.000000	0.000000	NaN	NaN	NaN	NaN	...	NaN
50%	NaN	4.000000	2.000000	971.000000	971.000000	0.000000	NaN	NaN	NaN	NaN	...	NaN
75%	NaN	8.000000	3.000000	2420.000000	2460.000000	0.000000	NaN	NaN	NaN	NaN	...	NaN
max	NaN	33.000000	6.000000	17350.000000	17350.000000	696.000000	NaN	NaN	NaN	NaN	...	NaN
std	NaN	6.884806	1.290777	3151.124186	3155.531241	83.220621	NaN	NaN	NaN	NaN	...	NaN

11 rows × 34 columns

```
Saved smallest cluster rows to ..\analysis_output
```