In [1]:
```python
# Import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import re
from datetime import datetime, timedelta
from scipy import stats
```

In [2]:
```python
# Set plotting style
plt.style.use('ggplot')
sns.set(style="whitegrid")
```

LOAD THE DATASETS

In [3]:
```python
# Read the transcation data into a pandas Dataframe
file_path = "D:/Quantium/"
transaction_data = pd.read_csv(file_path + "QVI_transaction_data.csv")
```

In [4]:
```python
# Convert DATE column from Excel-style integers to datetime
transaction_data['DATE'] = pd.to_datetime(transaction_data['DATE'], origi
```

In [18]:
```python
transaction_data.head(10)
```

Out[18]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PR
0	2018-10-17	1	1000	1	5	Natural Chip Compny SeaSalt175g	
1	2019-05-14	1	1307	348	66	CCs Nacho Cheese 175g	
2	2019-05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	
3	2018-08-17	2	2373	974	69	Smiths Chip Thinly S/ Cream&Onion 175g	
4	2018-08-18	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	
5	2019-05-19	4	4074	2982	57	Old El Paso Salsa Dip Tomato Mild 300g	
6	2019-05-16	4	4149	3333	16	Smiths Crinkle Chips Salt & Vinegar 330g	
7	2019-05-16	4	4196	3539	24	Grain Waves Sweet Chilli 210g	
8	2018-08-20	5	5026	4525	42	Doritos Corn Chip Mexican Jalapeno 150g	
9	2018-08-18	7	7150	6900	52	Grain Waves Sour Cream&Chives 210G	

In [9]:

```
# Read the customer data into a panda DataFrame
customer_data = pd.read_csv(file_path + "QVI_purchase_behaviour.csv")

customer_data.head()
```

Out[9]:

	LYLTY_CARD_NBR	LIFESTAGE	PREMIUM_CUSTOMER
0	1000	YOUNG SINGLES/COUPLES	Premium
1	1002	YOUNG SINGLES/COUPLES	Mainstream
2	1003	YOUNG FAMILIES	Budget
3	1004	OLDER SINGLES/COUPLES	Mainstream
4	1005	MIDAGE SINGLES/COUPLES	Mainstream

TEXT ANALYSIS ON PRODUCT NAMES TO VERIFY THEY ARE CHIPS

In [26]:

```
# Examine PROD_NAME to check we're looking at the right products
print(transaction_data['PROD_NAME'].value_counts().head(10))
```

```
PROD_NAME
Kettle Mozzarella   Basil & Pesto 175g      3304
Kettle Tortilla ChpsHny&Jlpno Chili 150g    3296
Cobs Popd Swt/Chlli &Sr/Cream Chips 110g    3269
Tyrrells Crisps     Ched & Chives 165g      3268
Cobs Popd Sea Salt  Chips 110g              3265
Kettle 135g Swt Pot Sea Salt                3257
Tostitos Splash Of  Lime 175g               3252
Infuzions Thai SweetChili PotatoMix 110g    3242
Smiths Crnkle Chip  Orgnl Big Bag 380g      3233
Thins Potato Chips  Hot & Spicy 175g        3229
Name: count, dtype: int64
```

In [ ]:
```python
# Extract all unique words from product names
all_product_words = ' '.join(transaction_data['PROD_NAME'].unique()).spli
product_words = pd.Series(all_product_words)
```

In [24]:
```python
# Remove digits and special characters from product words and count freque
clean_words = product_words[~product_words.str.contains(r'[0-9&]')]
word_counts = clean_words.value_counts().sort_values(ascending=False)
print("Most common words in product names:")
print(word_counts.head(20))
```

```
Most common words in product names:
Chips       21
Smiths      16
Crinkle     14
Cut         14
Kettle      13
Salt        12
Cheese      12
Original    10
Salsa        9
Chip         9
Doritos      9
Corn         8
Pringles     8
RRD          8
Chicken      7
WW           7
Sea          6
Sour         6
Vinegar      5
Crisps       5
Name: count, dtype: int64
```

In [25]:
```python
# Remove salsa products as we're only interested in chips
transaction_data['SALSA'] = transaction_data['PROD_NAME'].str.lower().str
transaction_data = transaction_data[~transaction_data['SALSA']].drop('SAL
```

CHECK THE NULL

In [27]:
```python
print("Null values in transaction data:")
transaction_data.isnull().sum()
```

```
Null values in transaction data:
```

Out[27]:
```
DATE              0
STORE_NBR         0
LYLTY_CARD_NBR    0
TXN_ID            0
PROD_NBR          0
PROD_NAME         0
PROD_QTY          0
TOT_SALES         0
dtype: int64
```

SUMARIZE DATASET

In [28]:
```
transaction_data.describe()
```

Out[28]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBI
count	246742	246742.000000	2.467420e+05	2.467420e+05	246742.00000
mean	2018-12-30 01:19:01.211467520	135.051098	1.355310e+05	1.351311e+05	56.35178
min	2018-07-01 00:00:00	1.000000	1.000000e+03	1.000000e+00	1.00000
25%	2018-09-30 00:00:00	70.000000	7.001500e+04	6.756925e+04	26.00000
50%	2018-12-30 00:00:00	130.000000	1.303670e+05	1.351830e+05	53.00000
75%	2019-03-31 00:00:00	203.000000	2.030840e+05	2.026538e+05	87.00000
max	2019-06-30 00:00:00	272.000000	2.373711e+06	2.415841e+06	114.00000
std	NaN	76.787096	8.071528e+04	7.814772e+04	33.69542

EXAMINE THE OUTLIERS

In [ ]:
```
# Investigate transaction with 200 packets of chips
outlier_transactions = transaction_data[transaction_data['PROD_QTY'] >= 2(
print("Outlier transactions:")
outlier_transactions
```

```
Outlier transactions:
```

Out[ ]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME
69762	2018-08-19	226	226000	226201	4	Dorito Corn Chp Supreme 380g
69763	2019-05-20	226	226000	226210	4	Dorito Corn Chp Supreme 380g

In [31]:
```
# Check if the customer with outlier transactions has other purchases
outlier_customer = outlier_transactions['LYLTY_CARD_NBR'].iloc[0]
customer_transactions = transaction_data[transaction_data['LYLTY_CARD_NBR
print(f"All transactions by customer {outlier_customer}:")
customer_transactions
```

```
All transactions by customer 226000:
```

Out[31]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME
69762	2018-08-19	226	226000	226201	4	Dorito Corn Chp Supreme 380g
69763	2019-05-20	226	226000	226210	4	Dorito Corn Chp Supreme 380g

In [32]:
```
# Filter out the outlier customer
transaction_data = transaction_data[transaction_data['LYLTY_CARD_NBR'] !=
print("Transaction data stats after removing outlier customer:")
transaction_data.describe()
```

```
Transaction data stats after removing outlier customer:
```

Out[32]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NB
count	246740	246740.000000	2.467400e+05	2.467400e+05	246740.00000
mean	2018-12-30 01:18:58.448569344	135.050361	1.355303e+05	1.351304e+05	56.35221
min	2018-07-01 00:00:00	1.000000	1.000000e+03	1.000000e+00	1.00000
25%	2018-09-30 00:00:00	70.000000	7.001500e+04	6.756875e+04	26.00000
50%	2018-12-30 00:00:00	130.000000	1.303670e+05	1.351815e+05	53.00000
75%	2019-03-31 00:00:00	203.000000	2.030832e+05	2.026522e+05	87.00000
max	2019-06-30 00:00:00	272.000000	2.373711e+06	2.415841e+06	114.00000
std	NaN	76.786971	8.071520e+04	7.814760e+04	33.69523

In [33]:
```
# Count transactions by date to check for data issues
transactions_by_day = transaction_data.groupby('DATE').size().reset_index
transactions_by_day.head()
```

Out[33]:

	DATE	N
0	2018-07-01	663
1	2018-07-02	650
2	2018-07-03	674
3	2018-07-04	669
4	2018-07-05	660

In [34]:
```
# Create a sequence of dates to identify any missing dates
date_range = pd.date_range(start='2018-07-01', end='2019-06-30')
date_df = pd.DataFrame({'DATE': date_range})
```

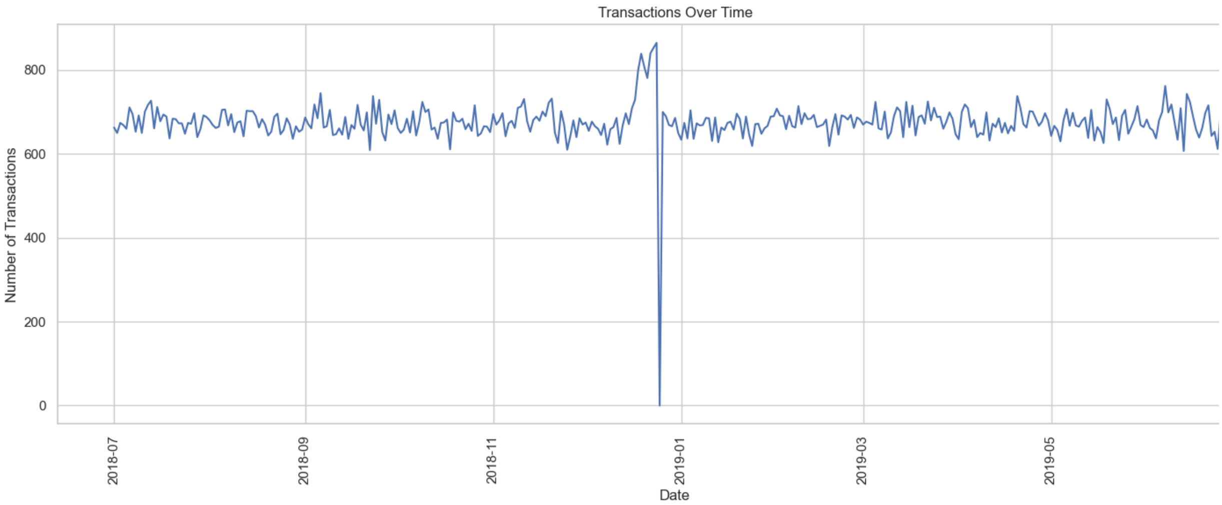
In [36]:
```
# Merge to find missing dates
transactions_by_day_full = pd.merge(date_df, transactions_by_day, on='DATI
print("Missing dates:")
transactions_by_day_full[transactions_by_day_full['N'] == 0]
```

Missing dates:

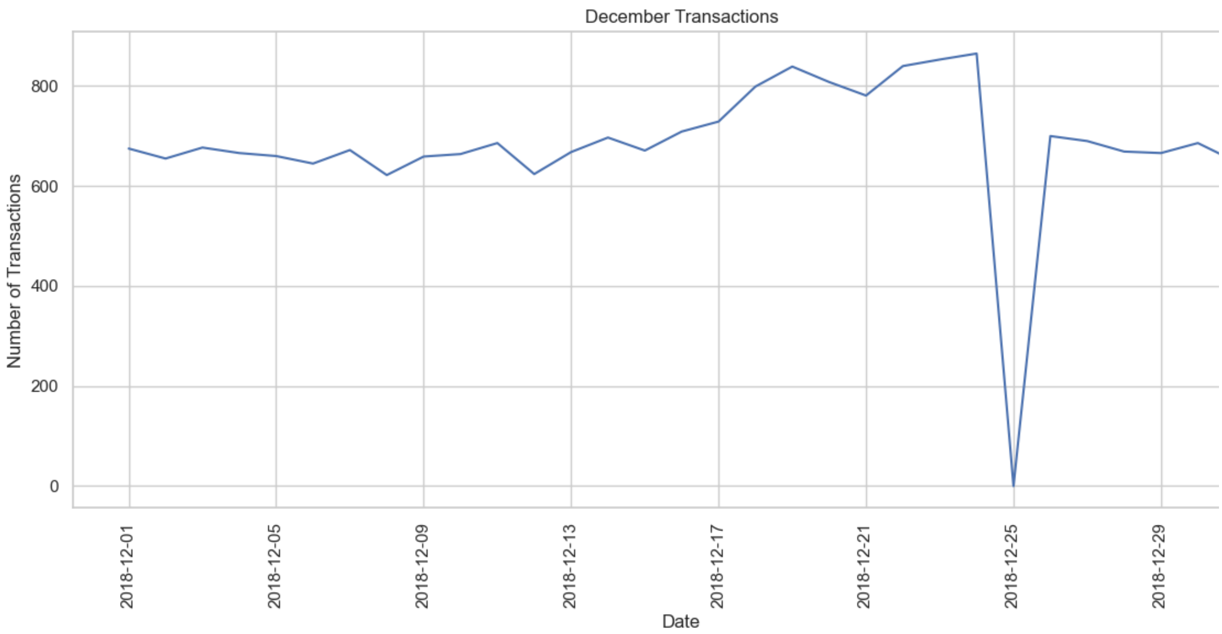
Out[36]:

	DATE	N
177	2018-12-25	0.0

In [37]:
```
# Plot transactions over time
plt.figure(figsize=(15, 6))
plt.plot(transactions_by_day_full['DATE'], transactions_by_day_full['N'])
plt.title('Transactions Over Time')
plt.xlabel('Date')
plt.ylabel('Number of Transactions')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```



In [38]:
```
# Zoom in on December data
dec_data = transactions_by_day_full[(transactions_by_day_full['DATE'] >=
                                     (transactions_by_day_full['DATE'] <= '
plt.figure(figsize=(12, 6))
plt.plot(dec_data['DATE'], dec_data['N'])
plt.title('December Transactions')
plt.xlabel('Date')
plt.ylabel('Number of Transactions')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```



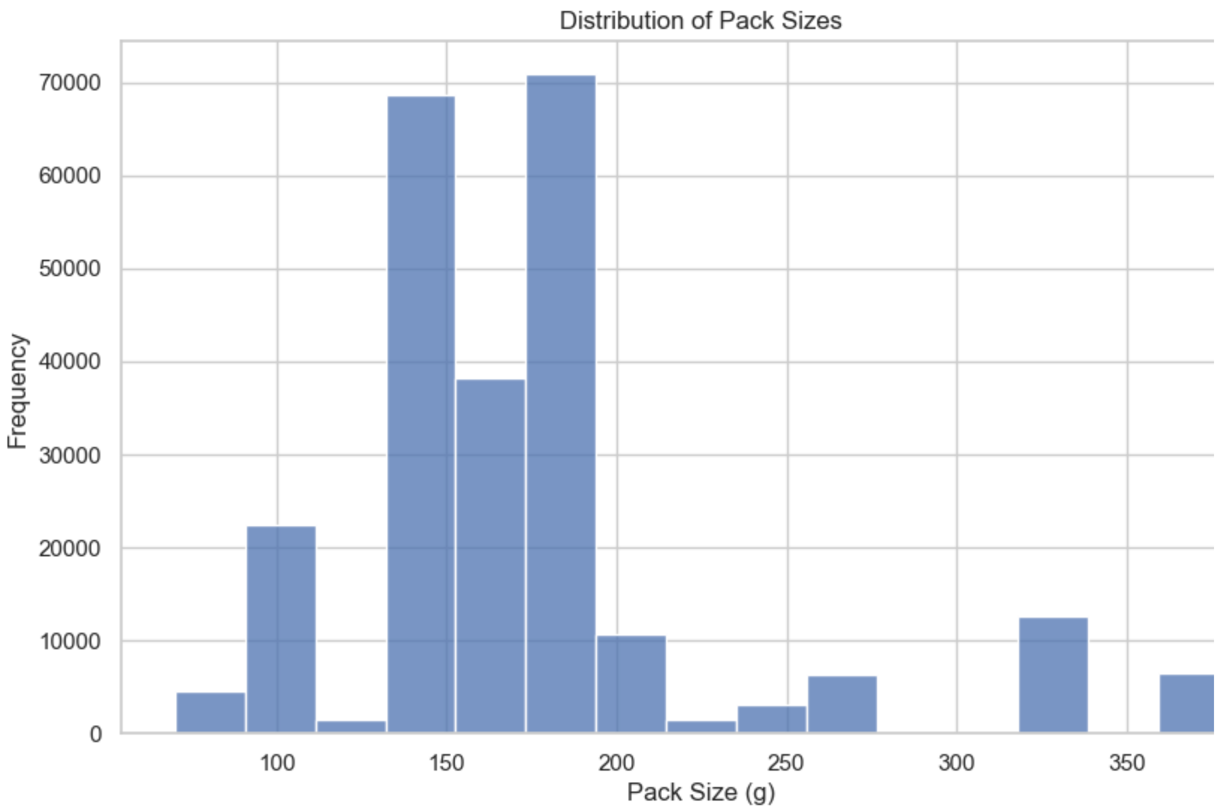

```
In [39]: # Create pack size from PROD_NAME
         def extract_pack_size(product_name):
             # Look for numbers in the product name
             match = re.search(r'(\d+)(g|kg|G|KG)', product_name)
             if match:
                 size = match.group(1)
                 unit = match.group(2).lower()
                 # Convert to grams if in kg
                 if unit == 'kg':
                     return int(float(size) * 1000)
                 return int(size)
             return None
```

```
In [40]: transaction_data['PACK_SIZE'] = transaction_data['PROD_NAME'].apply(extra
```

```
In [ ]: # Check pack sizes
        pack_size_counts = transaction_data['PACK_SIZE'].value_counts().sort_inde
        print("Pack size distribution:")
        print(pack_size_counts)
```

```
Pack size distribution:
PACK_SIZE
70       1507
90       3008
110     22387
125      1454
134     25102
135      3257
150     40203
160      2970
165     15297
170     19983
175     66390
180      1468
190      2995
200      4473
210      6272
220      1564
250      3169
270      6285
330     12540
380      6416
Name: count, dtype: int64
```

In [45]:
```
# Plot histogram of pack sizes
plt.figure(figsize=(10, 6))
sns.histplot(transaction_data['PACK_SIZE'], bins=15)
plt.title('Distribution of Pack Sizes')
plt.xlabel('Pack Size (g)')
plt.ylabel('Frequency')
plt.show()
```



In [46]:
```
# Extract brand from product name (first word)
transaction_data['BRAND'] = transaction_data['PROD_NAME'].apply(lambda x:
brand_counts = transaction_data['BRAND'].value_counts()
print("Brand distribution:")
print(brand_counts)
```

```
Brand distribution:
BRAND
Kettle        41288
Smiths        27390
Pringles      25102
Doritos       22041
Thins         14075
RRD           11894
Infuzions     11057
WW            10320
Cobs           9693
Tostitos       9471
Twisties       9454
Tyrrells       6442
Grain          6272
Natural        6050
Cheezels       4603
CCs            4551
Red            4427
Dorito         3183
Infzns         3144
Smith          2963
Cheetos        2927
Snbts          1576
Burger         1564
Woolworths     1516
GrnWves        1468
Sunbites       1432
NCC            1419
French         1418
Name: count, dtype: int64
```

In [51]:
```
# Clean brand names - combine similar brands
# RED and RRD are both Red Rock Deli
transaction_data.loc[transaction_data['BRAND'] == 'RED', 'BRAND'] = 'RRD'
# Add other brand adjustments if needed
# For example, if there are other variations like Dorito/Doritos:
# transaction_data.loc[transaction_data['BRAND'] == 'Dorito', 'BRAND'] =
```

In [52]:
```
# Check the cleaned brands
print("Cleaned brand distribution:")
print(transaction_data['BRAND'].value_counts())
```

```
Cleaned brand distribution:
BRAND
Kettle        41288
Smiths        27390
Doritos       25224
Pringles      25102
Thins         14075
RRD           11894
Infuzions     11057
WW            10320
Cobs           9693
Tostitos       9471
Twisties       9454
Tyrrells       6442
Grain          6272
Natural        6050
Cheezels       4603
CCs            4551
Red            4427
Infzns         3144
Smith          2963
Cheetos        2927
Snbts          1576
Burger         1564
Woolworths     1516
GrnWves        1468
Sunbites       1432
NCC            1419
French         1418
Name: count, dtype: int64
```

In [55]:
```
# Examine customer data
customer_data.head()
```

Out[55]:

	LYLTY_CARD_NBR	LIFESTAGE	PREMIUM_CUSTOMER
0	1000	YOUNG SINGLES/COUPLES	Premium
1	1002	YOUNG SINGLES/COUPLES	Mainstream
2	1003	YOUNG FAMILIES	Budget
3	1004	OLDER SINGLES/COUPLES	Mainstream
4	1005	MIDAGE SINGLES/COUPLES	Mainstream

In [56]:
```
customer_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 72637 entries, 0 to 72636
Data columns (total 3 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   LYLTY_CARD_NBR    72637 non-null  int64 
 1   LIFESTAGE         72637 non-null  object
 2   PREMIUM_CUSTOMER  72637 non-null  object
dtypes: int64(1), object(2)
memory usage: 1.7+ MB
```

In [57]:
```
customer_data.describe()
```

Out[57]:

	LYLTY_CARD_NBR
count	7.263700e+04
mean	1.361859e+05
std	8.989293e+04
min	1.000000e+03
25%	6.620200e+04
50%	1.340400e+05
75%	2.033750e+05
max	2.373711e+06

In [58]:
```
# Merge transaction data with customer data
data = pd.merge(transaction_data, customer_data, how='left')
```

In [60]:
```
# Check if all transactions have customer data
print("Number of transactions without customer data:")
data.isnull().sum()
```

```
Number of transactions without customer data:
```

Out[60]:
```
DATE                0
STORE_NBR           0
LYLTY_CARD_NBR      0
TXN_ID              0
PROD_NBR            0
PROD_NAME           0
PROD_QTY            0
TOT_SALES           0
PACK_SIZE           0
BRAND               0
LIFESTAGE           0
PREMIUM_CUSTOMER    0
dtype: int64
```

In [62]:
```
# Calculate total sales by customer segments
segment_sales = data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER'])['TOT_SALES
print("Total sales by customer segment:")
segment_sales
```

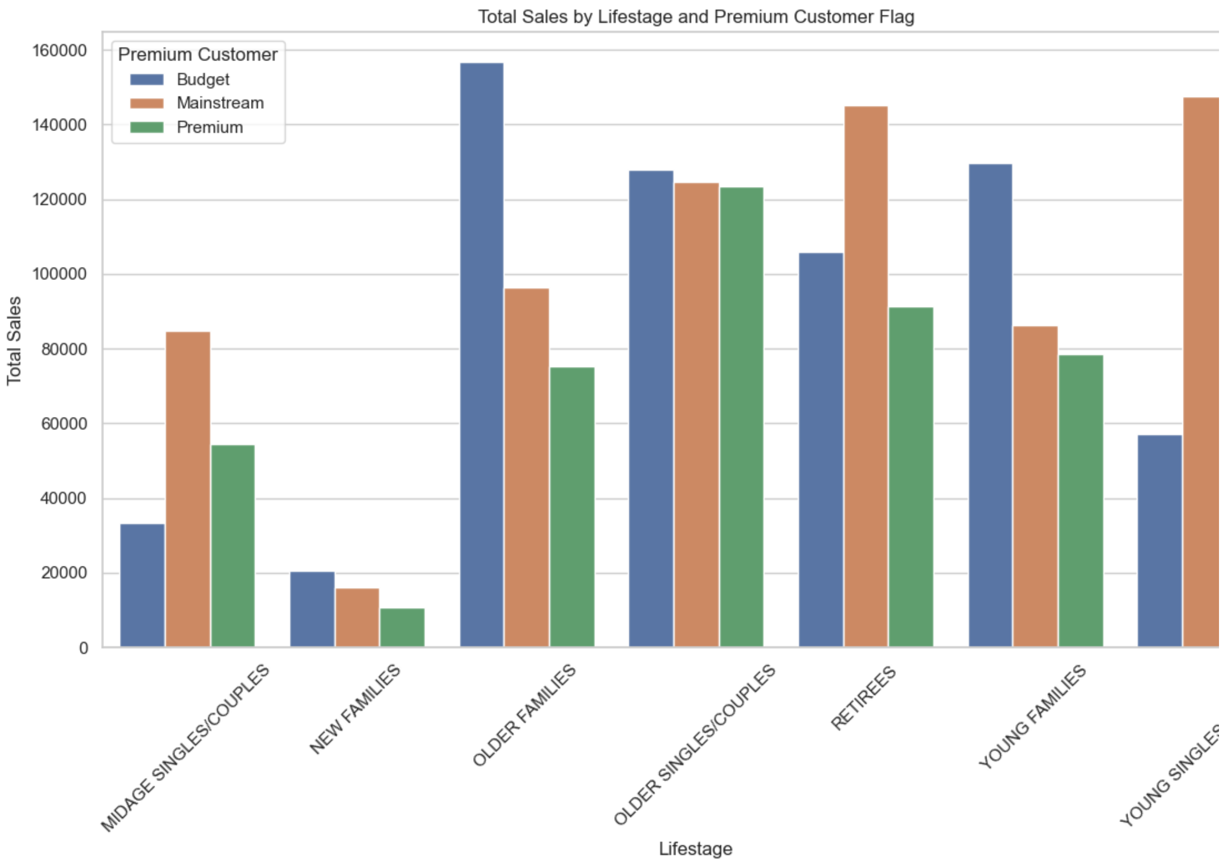
```
Total sales by customer segment:
```

Out[62]:

	LIFESTAGE	PREMIUM_CUSTOMER	TOT_SALES
0	MIDAGE SINGLES/COUPLES	Budget	33345.70
1	MIDAGE SINGLES/COUPLES	Mainstream	84734.25
2	MIDAGE SINGLES/COUPLES	Premium	54443.85
3	NEW FAMILIES	Budget	20607.45
4	NEW FAMILIES	Mainstream	15979.70
5	NEW FAMILIES	Premium	10760.80
6	OLDER FAMILIES	Budget	156863.75
7	OLDER FAMILIES	Mainstream	96413.55
8	OLDER FAMILIES	Premium	75242.60
9	OLDER SINGLES/COUPLES	Budget	127833.60
10	OLDER SINGLES/COUPLES	Mainstream	124648.50
11	OLDER SINGLES/COUPLES	Premium	123537.55
12	RETIREES	Budget	105916.30
13	RETIREES	Mainstream	145168.95
14	RETIREES	Premium	91296.65
15	YOUNG FAMILIES	Budget	129717.95
16	YOUNG FAMILIES	Mainstream	86338.25
17	YOUNG FAMILIES	Premium	78571.70
18	YOUNG SINGLES/COUPLES	Budget	57122.10
19	YOUNG SINGLES/COUPLES	Mainstream	147582.20
20	YOUNG SINGLES/COUPLES	Premium	39052.30

In [63]:

```
# Plot total sales by segment
plt.figure(figsize=(12, 8))
sns.barplot(x='LIFESTAGE', y='TOT_SALES', hue='PREMIUM_CUSTOMER', data=se
plt.title('Total Sales by Lifestage and Premium Customer Flag')
plt.xlabel('Lifestage')
plt.ylabel('Total Sales')
plt.xticks(rotation=45)
plt.legend(title='Premium Customer')
plt.tight_layout()
plt.show()
```




```
In [65]: # Count number of unique customers by segment
         customer_counts = data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER'])['LYLTY_(
         customer_counts.rename(columns={'LYLTY_CARD_NBR': 'CUSTOMER_COUNT'}, inpla
         print("Number of customers by segment:")
         customer_counts
```

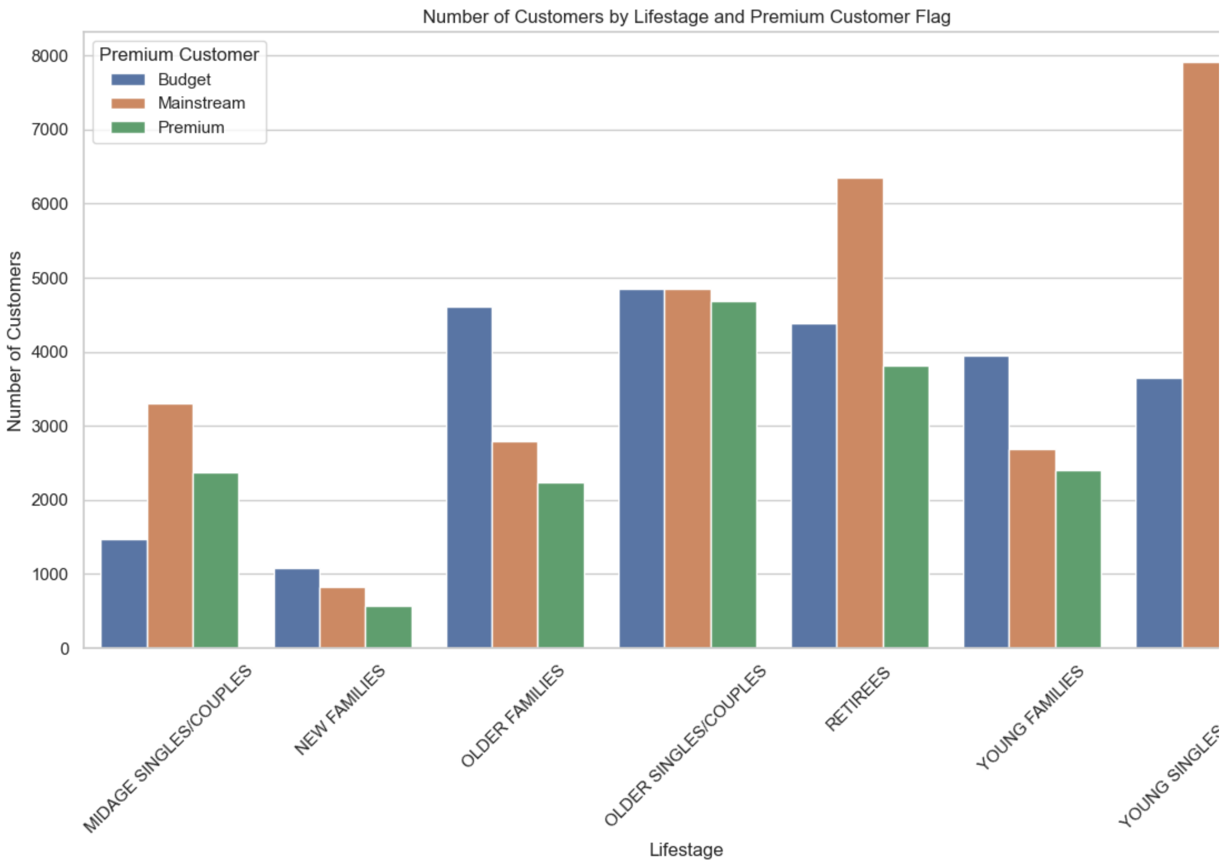
```
Number of customers by segment:
```

Out[65]:

	LIFESTAGE	PREMIUM_CUSTOMER	CUSTOMER_COUNT
0	MIDAGE SINGLES/COUPLES	Budget	1474
1	MIDAGE SINGLES/COUPLES	Mainstream	3298
2	MIDAGE SINGLES/COUPLES	Premium	2369
3	NEW FAMILIES	Budget	1087
4	NEW FAMILIES	Mainstream	830
5	NEW FAMILIES	Premium	575
6	OLDER FAMILIES	Budget	4611
7	OLDER FAMILIES	Mainstream	2788
8	OLDER FAMILIES	Premium	2231
9	OLDER SINGLES/COUPLES	Budget	4849
10	OLDER SINGLES/COUPLES	Mainstream	4858
11	OLDER SINGLES/COUPLES	Premium	4682
12	RETIREES	Budget	4385
13	RETIREES	Mainstream	6358
14	RETIREES	Premium	3812
15	YOUNG FAMILIES	Budget	3953
16	YOUNG FAMILIES	Mainstream	2685
17	YOUNG FAMILIES	Premium	2398
18	YOUNG SINGLES/COUPLES	Budget	3647
19	YOUNG SINGLES/COUPLES	Mainstream	7917
20	YOUNG SINGLES/COUPLES	Premium	2480

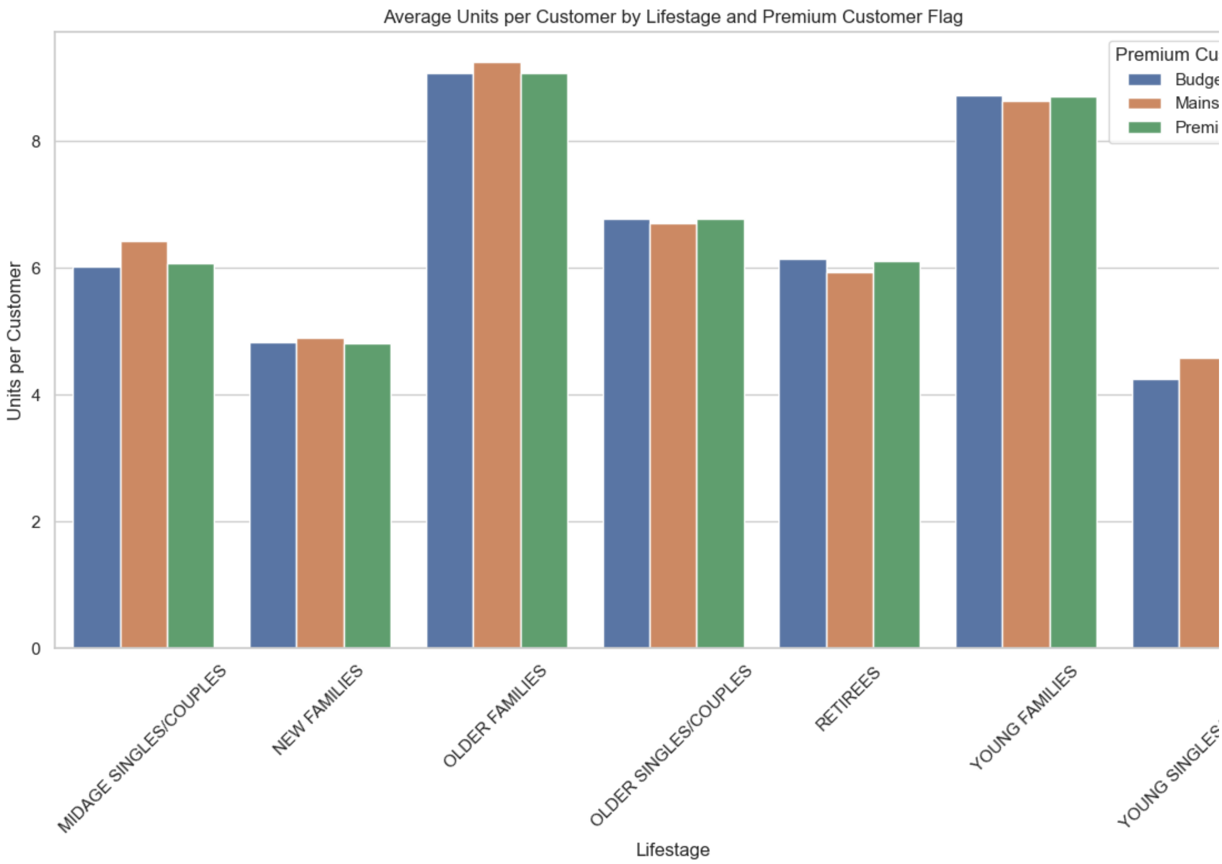
In [66]:

```
# Plot number of customers by segment
plt.figure(figsize=(12, 8))
sns.barplot(x='LIFESTAGE', y='CUSTOMER_COUNT', hue='PREMIUM_CUSTOMER', da
plt.title('Number of Customers by Lifestage and Premium Customer Flag')
plt.xlabel('Lifestage')
plt.ylabel('Number of Customers')
plt.xticks(rotation=45)
plt.legend(title='Premium Customer')
plt.tight_layout()
plt.show()
```



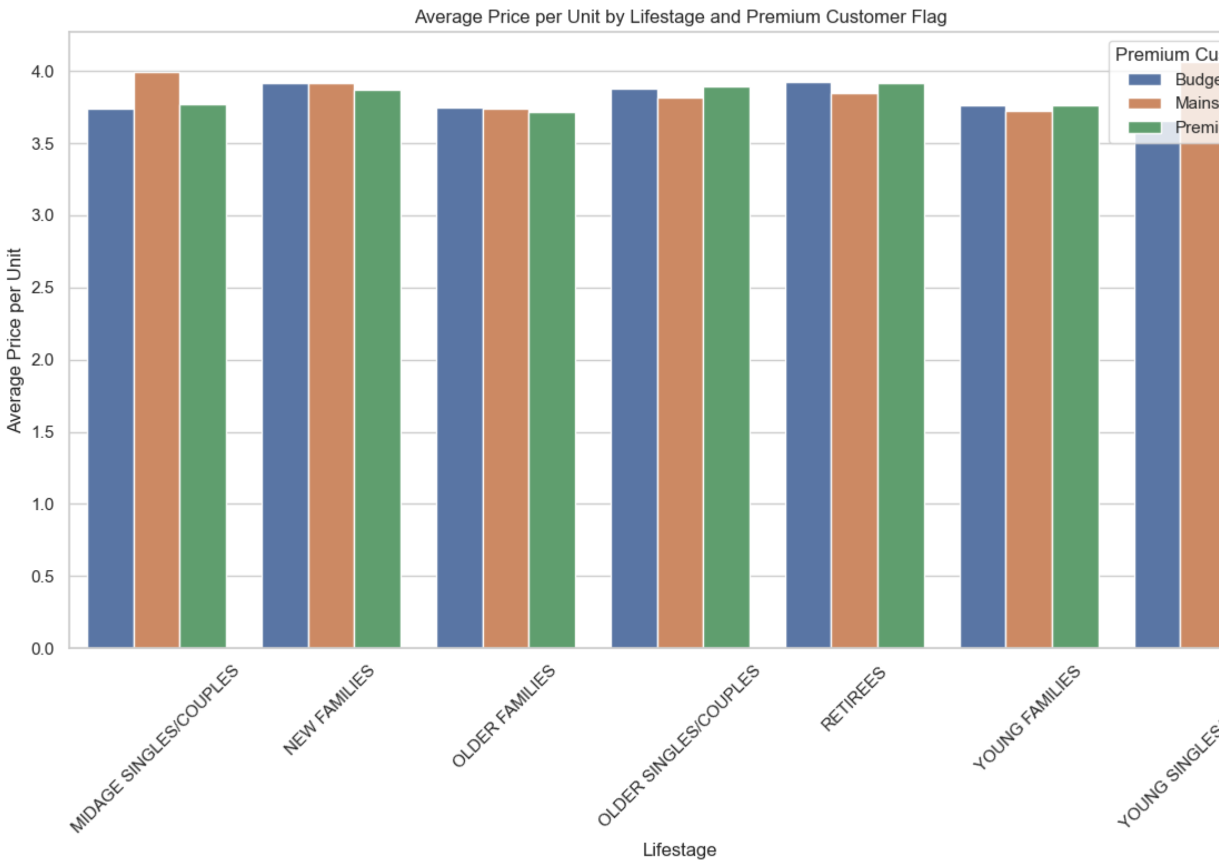

```
In [67]: # Calculate average units per customer by segment
         # First, get total units by segment
         segment_units = data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER'])['PROD_QTY
         # Merge with customer counts
         units_per_customer = pd.merge(segment_units, customer_counts)
         units_per_customer['UNITS_PER_CUSTOMER'] = units_per_customer['PROD_QTY']
```

```
In [68]: # Plot average units per customer by segment
         plt.figure(figsize=(12, 8))
         sns.barplot(x='LIFESTAGE', y='UNITS_PER_CUSTOMER', hue='PREMIUM_CUSTOMER'
         plt.title('Average Units per Customer by Lifestage and Premium Customer F
         plt.xlabel('Lifestage')
         plt.ylabel('Units per Customer')
         plt.xticks(rotation=45)
         plt.legend(title='Premium Customer')
         plt.tight_layout()
         plt.show()
```




```
In [69]: # Calculate average price per unit by segment
         data['PRICE_PER_UNIT'] = data['TOT_SALES'] / data['PROD_QTY']
         avg_price_by_segment = data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER'])['PI
```

```
In [70]: # Plot average price per unit by segment
         plt.figure(figsize=(12, 8))
         sns.barplot(x='LIFESTAGE', y='PRICE_PER_UNIT', hue='PREMIUM_CUSTOMER', da
         plt.title('Average Price per Unit by Lifestage and Premium Customer Flag'
         plt.xlabel('Lifestage')
         plt.ylabel('Average Price per Unit')
         plt.xticks(rotation=45)
         plt.legend(title='Premium Customer')
         plt.tight_layout()
         plt.show()
```




```
In [71]: # Statistical test: Comparing mainstream vs premium/budget for young sing
         # Filter data for the segments of interest
         target_segments = data[
             (data['LIFESTAGE'].isin(['YOUNG SINGLES/COUPLES', 'MIDAGE SINGLES/COU
             (data['PREMIUM_CUSTOMER'].isin(['Mainstream', 'Budget', 'Premium']))
         ]
```

```
In [72]: # Split into mainstream vs. others
         mainstream = target_segments[target_segments['PREMIUM_CUSTOMER'] == 'Main
         other = target_segments[target_segments['PREMIUM_CUSTOMER'] != 'Mainstrea
```

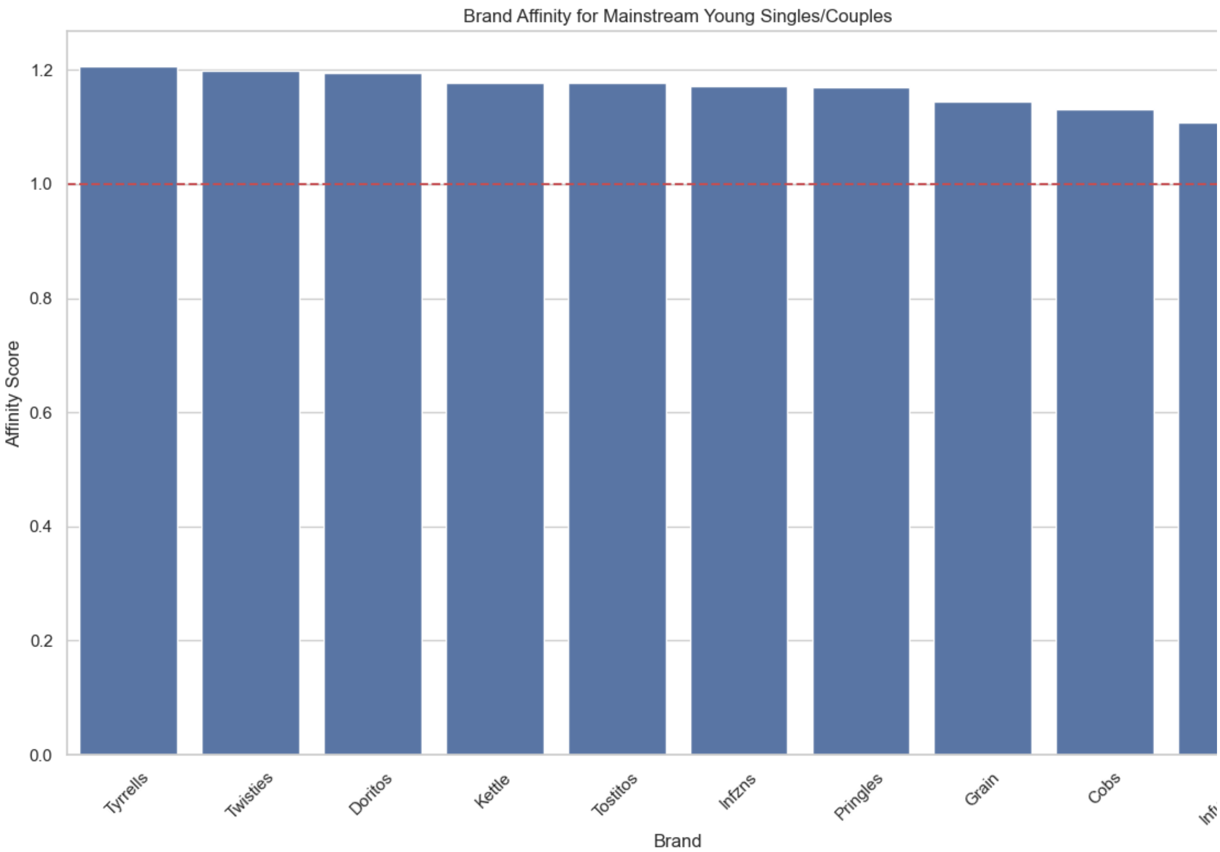
```
In [73]: # Perform t-test
         t_stat, p_value = stats.ttest_ind(mainstream, other, equal_var=False)
         print(f"T-test result: t-statistic = {t_stat}, p-value = {p_value}")
         significance = "significant" if p_value < 0.05 else "not significant"
         print(f"The difference in unit price is {significance} at the 5% level.")
```

```
T-test result: t-statistic = 37.6243885962295, p-value = 6.967354233018139e-3
The difference in unit price is significant at the 5% level.
```

```
In [74]: # Deep dive into Mainstream young singles/couples
         # Brand affinity analysis
         # Filter for the target segment
         target_segment = data[
             (data['LIFESTAGE'] == 'YOUNG SINGLES/COUPLES') &
             (data['PREMIUM_CUSTOMER'] == 'Mainstream')
         ]
```

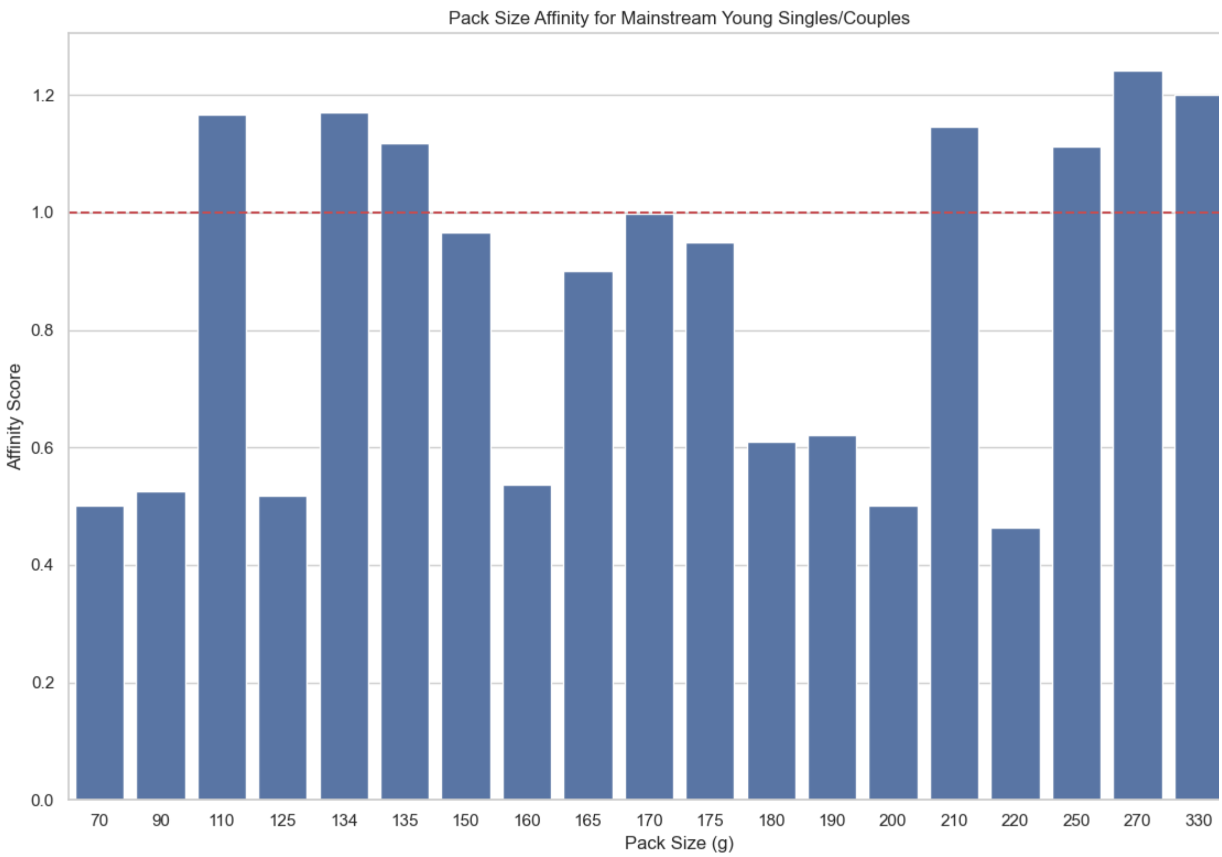
```
In [75]: # Count brands for target segment
         target_brands = target_segment.groupby('BRAND')['PROD_QTY'].sum().reset_i
         # Count brands for all customers
         total_brands = data.groupby('BRAND')['PROD_QTY'].sum().reset_index()
         # Merge to calculate affinity
         brand_affinity = pd.merge(target_brands, total_brands, on='BRAND', suffix
         brand_affinity['target_proportion'] = brand_affinity['PROD_QTY_target'] /
         brand_affinity['total_proportion'] = brand_affinity['PROD_QTY_total'] / b
         brand_affinity['affinity'] = brand_affinity['target_proportion'] / brand_
         brand_affinity = brand_affinity.sort_values('affinity', ascending=False)
```

```
In [76]: # Plot brand affinity
         plt.figure(figsize=(12, 8))
         sns.barplot(x='BRAND', y='affinity', data=brand_affinity.head(10))
         plt.title('Brand Affinity for Mainstream Young Singles/Couples')
         plt.xlabel('Brand')
         plt.ylabel('Affinity Score')
         plt.xticks(rotation=45)
         plt.axhline(y=1, color='r', linestyle='--')
         plt.tight_layout()
         plt.show()
```



In [77]:
```
# Pack size preference analysis
# Count pack sizes for target segment
target_pack_sizes = target_segment.groupby('PACK_SIZE')['PROD_QTY'].sum()
# Count pack sizes for all customers
total_pack_sizes = data.groupby('PACK_SIZE')['PROD_QTY'].sum().reset_inde
# Merge to calculate affinity
pack_size_affinity = pd.merge(target_pack_sizes, total_pack_sizes, on='PA
pack_size_affinity['target_proportion'] = pack_size_affinity['PROD_QTY_ta
pack_size_affinity['total_proportion'] = pack_size_affinity['PROD_QTY_tot
pack_size_affinity['affinity'] = pack_size_affinity['target_proportion'] /
pack_size_affinity = pack_size_affinity.sort_values('affinity', ascending
```

In [78]:
```
# Plot pack size affinity
plt.figure(figsize=(12, 8))
sns.barplot(x='PACK_SIZE', y='affinity', data=pack_size_affinity)
plt.title('Pack Size Affinity for Mainstream Young Singles/Couples')
plt.xlabel('Pack Size (g)')
plt.ylabel('Affinity Score')
plt.axhline(y=1, color='r', linestyle='--')
plt.tight_layout()
plt.show()
```



In [79]:
```
# Save the processed dataset for future tasks
data.to_csv(file_path + "QVI_data_processed.csv", index=False)
```

In [80]:
```
# Print key insights
print("\n--- KEY INSIGHTS ---")
print("1. Sales are mainly from Budget-older families, Mainstream-young s
print("2. Older families and young families generally buy more chips per
print("3. Mainstream young singles/couples tend to pay more per packet of
print(f"4. The t-test confirms that the price difference is {significance
print(f"5. Brands with highest affinity for Mainstream young singles/coup
print(f"6. Pack sizes with highest affinity for this segment: {', '.join(
```

--- KEY INSIGHTS ---
1. Sales are mainly from Budget-older families, Mainstream-young singles/coup
and Mainstream-retirees.
2. Older families and young families generally buy more chips per customer.
3. Mainstream young singles/couples tend to pay more per packet of chips.
4. The t-test confirms that the price difference is significant.
5. Brands with highest affinity for Mainstream young singles/couples: Tyrrell
Twisties, Doritos
6. Pack sizes with highest affinity for this segment: 270, 380, 330 grams