- **Quantium Virtual Internship- Retail Strategy and Analytics- Task 1**

```
# Importing the necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Loading the datasets
transaction_path = r"C:\Users\user\Desktop\#\portpolio projects\python\Retail Analytics\task_one\QVI_transaction_data.xlsx"
behaviour_path = r"C:\Users\user\Desktop\#\portpolio projects\python\Retail Analytics\task_one\QVI_purchase_behaviour.csv"

# Reading the transaction data (Excel)
transaction_data = pd.read_excel(transaction_path)

# Reading the customer behaviour data (CSV)
purchase_behaviour = pd.read_csv(behaviour_path)

# Previewing both datasets
print("Transaction Data:")
print(transaction_data.head(), "\n")

print("Purchase Behaviour Data:")
print(purchase_behaviour.head())
```

```
Transaction Data:
    DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
0  43390          1            1000       1         5
1  43599          1            1307     348        66
2  43605          1            1343     383        61
3  43329          2            2373     974        69
4  43330          2            2426    1038       108

                                PROD_NAME  PROD_QTY  TOT_SALES
0    Natural Chip        Compny SeaSalt175g         2        6.0
1                  CCs Nacho Cheese    175g         3        6.3
2    Smiths Crinkle Cut  Chips Chicken 170g         2        2.9
3    Smiths Chip Thinly  S/Cream&Onion 175g         5       15.0
4  Kettle Tortilla ChpsHny&Jlpno Chili 150g         3       13.8

Purchase Behaviour Data:
   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
```

```
# Standardizing column names (remove spaces, make lowercase)
transaction_data.columns = transaction_data.columns.str.strip().str.upper()
purchase_behaviour.columns = purchase_behaviour.columns.str.strip().str.upper()

# Check for missing values
print("Missing values in transaction data:\n", transaction_data.isnull().sum())
print("\nMissing values in behaviour data:\n", purchase_behaviour.isnull().sum())

# Check for duplicates
print("\nDuplicate rows in transaction data:", transaction_data.duplicated().sum())
print("Duplicate rows in behaviour data:", purchase_behaviour.duplicated().sum())
```

```
Missing values in transaction data:
 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

Missing values in behaviour data:
 LYLTY_CARD_NBR      0
LIFESTAGE           0
PREMIUM_CUSTOMER    0
```

```
dtype: int64

Duplicate rows in transaction data: 1
Duplicate rows in behaviour data: 0
```

```
# Drop the duplicate row
transaction_data = transaction_data.drop_duplicates()

# Confirm removal
print("Duplicate rows after cleaning:", transaction_data.duplicated().sum())
```

```
Duplicate rows after cleaning: 0
```

```
#  merging on LYLTY_CARD_NBR
merged_df = pd.merge(transaction_data, purchase_behaviour, how='left', on='LYLTY_CARD_NBR')

# Confirm the merge
print("Merged Data Shape:", merged_df.shape)
print("Sample of merged data:\n", merged_df.head())
```

```
Merged Data Shape: (264835, 10)
Sample of merged data:
     DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
0  43390          1            1000       1         5
1  43599          1            1307     348        66
2  43605          1            1343     383        61
3  43329          2            2373     974        69
4  43330          2            2426    1038       108

                                PROD_NAME  PROD_QTY  TOT_SALES  \
0    Natural Chip        Compny SeaSalt175g         2        6.0
1                  CCs Nacho Cheese    175g         3        6.3
2    Smiths Crinkle Cut  Chips Chicken 170g         2        2.9
3    Smiths Chip Thinly  S/Cream&Onion 175g         5       15.0
4  Kettle Tortilla ChpsHny&Jlpno Chili 150g         3       13.8

               LIFESTAGE PREMIUM_CUSTOMER
0   YOUNG SINGLES/COUPLES          Premium
1  MIDAGE SINGLES/COUPLES           Budget
2  MIDAGE SINGLES/COUPLES           Budget
3  MIDAGE SINGLES/COUPLES           Budget
4  MIDAGE SINGLES/COUPLES           Budget
```

```
# Checking for missing values in the merged dataset
missing_report = merged_df.isnull().sum()
missing_report = missing_report[missing_report > 0]
print("Columns with missing values:\n", missing_report)
```

```
Columns with missing values:
 Series([], dtype: int64)
```

```
merged_df.head()
# Saving the merged dataset to a new Excel file
```

| | DATE | STORE_NBR | LYLTY_CARD_NBR | TXN_ID | PROD_NBR | PROD_NAME | PROD_QTY | TOT_SALES | LIFESTAGE | PREMIUM_CUSTOMER |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 43390 | 1 | 1000 | 1 | 5 | Natural Chip Compny SeaSalt175g | 2 | 6.0 | YOUNG SINGLES/COUPLES | Premium |
| **1** | 43599 | 1 | 1307 | 348 | 66 | CCs Nacho Cheese 175g | 3 | 6.3 | MIDAGE SINGLES/COUPLES | Budget |
| **2** | 43605 | 1 | 1343 | 383 | 61 | Smiths Crinkle Cut Chips Chicken 170g | 2 | 2.9 | MIDAGE SINGLES/COUPLES | Budget |
| **3** | 43329 | 2 | 2373 | 974 | 69 | Smiths Chip Thinly S/Cream&Onion 175g | 5 | 15.0 | MIDAGE SINGLES/COUPLES | Budget |
| **4** | 43330 | 2 | 2426 | 1038 | 108 | Kettle Tortilla ChpsHny&Jlpno Chili 150g | 3 | 13.8 | MIDAGE SINGLES/COUPLES | Budget |

```
merged_df['PROD_NAME']
```

```
0          Natural Chip        Compny SeaSalt175g
1                        CCs Nacho Cheese    175g
2          Smiths Crinkle Cut  Chips Chicken 170g
```

```
3          Smiths Chip Thinly  S/Cream&Onion 175g
4        Kettle Tortilla ChpsHny&Jlpno Chili 150g
                          ...
264830    Kettle Sweet Chilli And Sour Cream 175g
264831              Tostitos Splash Of  Lime 175g
264832                   Doritos Mexicana    170g
264833    Doritos Corn Chip Mexican Jalapeno 150g
264834              Tostitos Splash Of  Lime 175g
Name: PROD_NAME, Length: 264835, dtype: object
```

```
# Breaking down product name into brand, flavour, and pack size
merged_df[['brand', 'flavour', 'pack_size']] = merged_df['PROD_NAME'].str.rsplit(' ', n=2, expand=True)
```

```
merged_df.head()
```

| | DATE | STORE_NBR | LYLTY_CARD_NBR | TXN_ID | PROD_NBR | PROD_NAME | PROD_QTY | TOT_SALES | LIFESTAGE | PREMIUM_CUSTOMER | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 43390 | 1 | 1000 | 1 | 5 | Natural Chip Compny SeaSalt175g | 2 | 6.0 | YOUNG SINGLES/COUPLES | Premium | Natura |
| **1** | 43599 | 1 | 1307 | 348 | 66 | CCs Nacho Cheese 175g | 3 | 6.3 | MIDAGE SINGLES/COUPLES | Budget | CCs N C |
| **2** | 43605 | 1 | 1343 | 383 | 61 | Smiths Crinkle Cut Chips Chicken 170g | 2 | 2.9 | MIDAGE SINGLES/COUPLES | Budget | Smiths C Cut |
| **3** | 43329 | 2 | 2373 | 974 | 69 | Smiths Chip Thinly S/Cream&Onion 175g | 5 | 15.0 | MIDAGE SINGLES/COUPLES | Budget | Smiths |
| **4** | 43330 | 2 | 2426 | 1038 | 108 | Kettle Tortilla ChpsHny&Jlpno Chili 150g | 3 | 13.8 | MIDAGE SINGLES/COUPLES | Budget | Kettle T ChpsHny& |

```
merged_df.columns
```

```
Index(['DATE', 'STORE_NBR', 'LYLTY_CARD_NBR', 'TXN_ID', 'PROD_NBR',
       'PROD_NAME', 'PROD_QTY', 'TOT_SALES', 'LIFESTAGE', 'PREMIUM_CUSTOMER',
       'brand', 'flavour', 'pack_size'],
      dtype='object')
```

## 🔀 Rearranging Columns for Logical Flow

```
# Renaming columns
merged_df.rename(columns={
    'DATE': 'transaction_date',
    'STORE_NBR': 'store_number',
    'LYLTY_CARD_NBR': 'customer_id',
    'TXN_ID': 'transaction_id',
    'PROD_NBR': 'product_id',
    'PROD_NAME': 'product_name',
    'PROD_QTY': 'quantity',
    'TOT_SALES': 'total_sales',
    'LIFESTAGE': 'lifestage',
    'PREMIUM_CUSTOMER': 'premium_customer',
    'pack_size': 'pack_size_grams'
}, inplace=True)

# Reordering columns
merged_df = merged_df[[
    'transaction_date',
    'transaction_id',
    'customer_id',
    'store_number',
    'product_id',
    'product_name',
    'brand',
    'flavour',
    'pack_size_grams',
    'quantity',
    'total_sales',
```

```
    'lifestage',
    'premium_customer'
]]

# Preview to confirm
print(merged_df.head())
```

```
   transaction_date  transaction_id  customer_id  store_number  product_id  \
0             43390               1         1000             1           5
1             43599             348         1307             1          66
2             43605             383         1343             1          61
3             43329             974         2373             2          69
4             43330            1038         2426             2         108

                              product_name                         brand  \
0    Natural Chip        Compny SeaSalt175g           Natural Chip
1                  CCs Nacho Cheese    175g             CCs Nacho Cheese
2    Smiths Crinkle Cut  Chips Chicken 170g     Smiths Crinkle Cut  Chips
3    Smiths Chip Thinly  S/Cream&Onion 175g           Smiths Chip Thinly
4  Kettle Tortilla ChpsHny&Jlpno Chili 150g  Kettle Tortilla ChpsHny&Jlpno

         flavour pack_size_grams  quantity  total_sales  \
0         Compny     SeaSalt175g         2          6.0
1                         175g         3          6.3
2        Chicken            170g         2          2.9
3  S/Cream&Onion            175g         5         15.0
4          Chili            150g         3         13.8

               lifestage premium_customer
0   YOUNG SINGLES/COUPLES          Premium
1  MIDAGE SINGLES/COUPLES           Budget
2  MIDAGE SINGLES/COUPLES           Budget
3  MIDAGE SINGLES/COUPLES           Budget
4  MIDAGE SINGLES/COUPLES           Budget
```

```
merged_df.head()
```

| | transaction_date | transaction_id | customer_id | store_number | product_id | product_name | brand | flavour | pack_size_grams |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 43390 | 1 | 1000 | 1 | 5 | Natural Chip Compny SeaSalt175g | Natural Chip | Compny | SeaSalt175g |
| **1** | 43599 | 348 | 1307 | 1 | 66 | CCs Nacho Cheese 175g | CCs Nacho Cheese | | 175g |
| **2** | 43605 | 383 | 1343 | 1 | 61 | Smiths Crinkle Cut Chips Chicken 170g | Smiths Crinkle Cut Chips | Chicken | 170g |
| **3** | 43329 | 974 | 2373 | 2 | 69 | Smiths Chip Thinly S/Cream&Onion 175g | Smiths Chip Thinly | S/Cream&Onion | 175g |
| **4** | 43330 | 1038 | 2426 | 2 | 108 | Kettle Tortilla ChpsHny&Jlpno Chili 150g | Kettle Tortilla ChpsHny&Jlpno | Chili | 150g |

```
merged_df['premium_customer'].unique()
```

```
array(['Premium', 'Budget', 'Mainstream'], dtype=object)
```

```
# Renaming for semantic clarity
merged_df.rename(columns={'premium_customer': 'customer_type'}, inplace=True)
```

```
merged_df.head()
```

| | transaction_date | transaction_id | customer_id | store_number | product_id | product_name | brand | flavour | pack_size_grams |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 43390 | 1 | 1000 | 1 | 5 | Natural Chip Compny SeaSalt175g | Natural Chip | Compny | SeaSalt175g |
| **1** | 43599 | 348 | 1307 | 1 | 66 | CCs Nacho Cheese 175g | CCs Nacho Cheese | | 175g |
| **2** | 43605 | 383 | 1343 | 1 | 61 | Smiths Crinkle Cut Chips Chicken 170g | Smiths Crinkle Cut Chips | Chicken | 170g |
| **3** | 43329 | 974 | 2373 | 2 | 69 | Smiths Chip Thinly S/Cream&Onion 175g | Smiths Chip Thinly | S/Cream&Onion | 175g |
| **4** | 43330 | 1038 | 2426 | 2 | 108 | Kettle Tortilla ChpsHny&Jlpno Chili 150g | Kettle Tortilla ChpsHny&Jlpno | Chili | 150g |

```
merged_df['lifestage'].unique()
```

```
array(['YOUNG SINGLES/COUPLES', 'MIDAGE SINGLES/COUPLES', 'NEW FAMILIES',
       'OLDER FAMILIES', 'OLDER SINGLES/COUPLES', 'RETIREES',
       'YOUNG FAMILIES'], dtype=object)
```

```
# Converting 'lifestage' values to title case for professionalism and clarity
merged_df['lifestage'] = merged_df['lifestage'].str.title().str.strip()
```

```
merged_df['lifestage'].unique()
```

```
array(['Young Singles/Couples', 'Midage Singles/Couples', 'New Families',
       'Older Families', 'Older Singles/Couples', 'Retirees',
       'Young Families'], dtype=object)
```

```
merged_df.head()
```

| | transaction_date | transaction_id | customer_id | store_number | product_id | product_name | brand | flavour | pack_size_grams |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 43390 | 1 | 1000 | 1 | 5 | Natural Chip Compny SeaSalt175g | Natural Chip | Compny | 175.0 |
| **1** | 43599 | 348 | 1307 | 1 | 66 | CCs Nacho Cheese 175g | CCs Nacho Cheese | | 175.0 |
| **2** | 43605 | 383 | 1343 | 1 | 61 | Smiths Crinkle Cut Chips Chicken 170g | Smiths Crinkle Cut Chips | Chicken | 170.0 |
| **3** | 43329 | 974 | 2373 | 2 | 69 | Smiths Chip Thinly S/Cream&Onion 175g | Smiths Chip Thinly | S/Cream&Onion | 175.0 |
| **4** | 43330 | 1038 | 2426 | 2 | 108 | Kettle Tortilla ChpsHny&Jlpno Chili 150g | Kettle Tortilla ChpsHny&Jlpno | Chili | 150.0 |

```
# Extracting pack size as numeric grams from product_name
merged_df['pack_size_grams'] = merged_df['product_name'].str.extract(r'(\d+)[Gg]').astype(float)
```

```
merged_df.head()
```

| | transaction_date | transaction_id | customer_id | store_number | product_id | product_name | brand | flavour | pack_size_grams |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 43390 | 1 | 1000 | 1 | 5 | Natural Chip Compny SeaSalt175g | Natural Chip | Compny | 175.0 |
| 1 | 43599 | 348 | 1307 | 1 | 66 | CCs Nacho Cheese 175g | CCs Nacho Cheese | | 175.0 |
| 2 | 43605 | 383 | 1343 | 1 | 61 | Smiths Crinkle Cut Chips Chicken 170g | Smiths Crinkle Cut Chips | Chicken | 170.0 |
| 3 | 43329 | 974 | 2373 | 2 | 69 | Smiths Chip Thinly S/Cream&Onion 175g | Smiths Chip Thinly | S/Cream&Onion | 175.0 |
| 4 | 43330 | 1038 | 2426 | 2 | 108 | Kettle Tortilla ChpsHny&Jlpno Chili 150g | Kettle Tortilla ChpsHny&Jlpno | Chili | 150.0 |

```
# Inspect unextracted rows
unmatched_pack_sizes = merged_df[merged_df['pack_size_grams'].isna()]
print(unmatched_pack_sizes[['product_name']].drop_duplicates())
```

```
Empty DataFrame
Columns: [product_name]
Index: []
```

```
merged_df.head()
```

| | transaction_date | transaction_id | customer_id | store_number | product_id | product_name | brand | flavour | pack_size_grams |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 43390 | 1 | 1000 | 1 | 5 | Natural Chip Compny SeaSalt175g | Natural Chip | Compny | 175.0 |
| 1 | 43599 | 348 | 1307 | 1 | 66 | CCs Nacho Cheese 175g | CCs Nacho Cheese | | 175.0 |
| 2 | 43605 | 383 | 1343 | 1 | 61 | Smiths Crinkle Cut Chips Chicken 170g | Smiths Crinkle Cut Chips | Chicken | 170.0 |
| 3 | 43329 | 974 | 2373 | 2 | 69 | Smiths Chip Thinly S/Cream&Onion 175g | Smiths Chip Thinly | S/Cream&Onion | 175.0 |
| 4 | 43330 | 1038 | 2426 | 2 | 108 | Kettle Tortilla ChpsHny&Jlpno Chili 150g | Kettle Tortilla ChpsHny&Jlpno | Chili | 150.0 |

## ✅ Full Column Format Optimization

```
# Converting 'transaction_date' to datetime format
merged_df['transaction_date'] = pd.to_datetime(merged_df['transaction_date'])

# Ensuring ID fields are treated as string (not integers, to preserve leading zeros)
merged_df['transaction_id'] = merged_df['transaction_id'].astype(str)
merged_df['customer_id'] = merged_df['customer_id'].astype(str)
merged_df['store_number'] = merged_df['store_number'].astype(str)
merged_df['product_id'] = merged_df['product_id'].astype(str)

# Standardizing text fields to Title Case and stripping whitespaces
merged_df['product_name'] = merged_df['product_name'].str.strip().str.title()
merged_df['brand'] = merged_df['brand'].str.strip().str.title()
merged_df['flavour'] = merged_df['flavour'].str.strip().str.title()
merged_df['lifestage'] = merged_df['lifestage'].str.strip().str.title()
merged_df['customer_type'] = merged_df['customer_type'].str.strip().str.title()

# Making sure pack size and sales figures are numeric
merged_df['pack_size_grams'] = pd.to_numeric(merged_df['pack_size_grams'], errors='coerce')
```

```
merged_df['quantity'] = pd.to_numeric(merged_df['quantity'], errors='coerce')
merged_df['total_sales'] = pd.to_numeric(merged_df['total_sales'], errors='coerce')
```

```
merged_df.dtypes
```

```
transaction_date    datetime64[ns]
transaction_id              object
customer_id                 object
store_number                object
product_id                  object
product_name                object
brand                       object
flavour                     object
pack_size_grams            float64
quantity                     int64
total_sales                float64
lifestage                   object
customer_type               object
dtype: object
```

```
# Convert the timestamp in nanoseconds to integer days
merged_df['transaction_date'] = pd.to_datetime(merged_df['transaction_date'].astype('int64'), origin='unix', unit='ns')
```

```
# Try coercing the column if the above fails
merged_df['transaction_date'] = pd.to_datetime(merged_df['transaction_date'], errors='coerce')
```

```
# Re-loading the original Excel data with transaction_date NOT parsed as datetime
transaction_df = pd.read_excel(
    r"C:\Users\user\Desktop\#\portpolio projects\python\Retail Analytics\task_one\QVI_transaction_data.xlsx",
    dtype={'DATE': 'int64'}  # Make sure DATE column stays as integer
)
```

```
# Converting Excel serial date (e.g. 43390) to datetime
transaction_df['DATE'] = pd.to_datetime(transaction_df['DATE'], origin='1899-12-30', unit='D')
```

```
# Replace the broken transaction_date in merged_df
merged_df['transaction_date'] = pd.to_datetime(transaction_df['DATE'])
```

```
print(merged_df['transaction_date'].min(), merged_df['transaction_date'].max())
print(merged_df['transaction_date'].dt.year.unique())
```

```
2018-07-01 00:00:00 2019-06-30 00:00:00
[2018 2019]
```

```
merged_df.head()
```

| | transaction_date | transaction_id | customer_id | store_number | product_id | product_name | brand | flavour | pack_size_grams |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 2018-10-17 | 1 | 1000 | 1 | 5 | Natural Chip Compny Seasalt175G | Natural Chip | Compny | 175.0 |
| **1** | 2019-05-14 | 348 | 1307 | 1 | 66 | Ccs Nacho Cheese 175G | Ccs Nacho Cheese | | 175.0 |
| **2** | 2019-05-20 | 383 | 1343 | 1 | 61 | Smiths Crinkle Cut Chips Chicken 170G | Smiths Crinkle Cut Chips | Chicken | 170.0 |
| **3** | 2018-08-17 | 974 | 2373 | 2 | 69 | Smiths Chip Thinly S/Cream&Onion 175G | Smiths Chip Thinly | S/Cream&Onion | 175.0 |
| **4** | 2018-08-18 | 1038 | 2426 | 2 | 108 | Kettle Tortilla Chpshny&Jlpno Chili 150G | Kettle Tortilla Chpshny&Jlpno | Chili | 150.0 |

```
print(merged_df['transaction_date'].head())
print(merged_df['transaction_date'].describe())
```

```
0   1970-01-01 00:00:00.000043390
1   1970-01-01 00:00:00.000043599
2   1970-01-01 00:00:00.000043605
3   1970-01-01 00:00:00.000043329
4   1970-01-01 00:00:00.000043330
Name: transaction_date, dtype: datetime64[ns]
count                         264835
mean     1970-01-01 00:00:00.000043464
min      1970-01-01 00:00:00.000043282
25%      1970-01-01 00:00:00.000043373
50%      1970-01-01 00:00:00.000043464
75%      1970-01-01 00:00:00.000043555
max      1970-01-01 00:00:00.000043646
Name: transaction_date, dtype: object
```

```
merged_df.head().count
```

```
<bound method DataFrame.count of   transaction_date transaction_id customer_id store_number product_id  \
0       2018-10-17              1        1000            1          5
1       2019-05-14            348        1307            1         66
2       2019-05-20            383        1343            1         61
3       2018-08-17            974        2373            2         69
4       2018-08-18           1038        2426            2        108

                            product_name                       brand  \
0    Natural Chip        Compny Seasalt175G                Natural Chip
1                  Ccs Nacho Cheese    175G              Ccs Nacho Cheese
2    Smiths Crinkle Cut  Chips Chicken 170G     Smiths Crinkle Cut  Chips
3    Smiths Chip Thinly  S/Cream&Onion 175G             Smiths Chip Thinly
4  Kettle Tortilla Chpshny&Jlpno Chili 150G  Kettle Tortilla Chpshny&Jlpno

         flavour  pack_size_grams  quantity  total_sales  \
0         Compny            175.0         2          6.0
1                           175.0         3          6.3
2        Chicken            170.0         2          2.9
3  S/Cream&Onion            175.0         5         15.0
4          Chili            150.0         3         13.8

                lifestage customer_type
0   Young Singles/Couples       Premium
1  Midage Singles/Couples        Budget
2  Midage Singles/Couples        Budget
3  Midage Singles/Couples        Budget
4  Midage Singles/Couples        Budget  >
```

```
merged_df.info
```

```
<bound method DataFrame.info of        transaction_date transaction_id customer_id store_number product_id  \
0            2018-10-17              1        1000            1          5
1            2019-05-14            348        1307            1         66
2            2019-05-20            383        1343            1         61
3            2018-08-17            974        2373            2         69
4            2018-08-18           1038        2426            2        108
...                 ...            ...         ...          ...        ...
```

```
264830       2018-11-12         270088      272319          272         89
264831       2019-03-09         270154      272358          272         74
264832       2018-08-13         270187      272379          272         51
264833       2018-11-06         270188      272379          272         42
264834       2018-12-27         270189      272380          272         74

                                    product_name  \
0         Natural Chip        Compny Seasalt175G
1                       Ccs Nacho Cheese    175G
2         Smiths Crinkle Cut  Chips Chicken 170G
3         Smiths Chip Thinly  S/Cream&Onion 175G
4       Kettle Tortilla Chpshny&Jlpno Chili 150G
...                                      ...
264830   Kettle Sweet Chilli And Sour Cream 175G
264831             Tostitos Splash Of  Lime 175G
264832                  Doritos Mexicana    170G
264833   Doritos Corn Chip Mexican Jalapeno 150G
264834             Tostitos Splash Of  Lime 175G

                               brand        flavour  pack_size_grams  \
0                       Natural Chip         Compny            175.0
1                    Ccs Nacho Cheese                           175.0
2          Smiths Crinkle Cut  Chips        Chicken            170.0
3                  Smiths Chip Thinly  S/Cream&Onion            175.0
4       Kettle Tortilla Chpshny&Jlpno          Chili            150.0
...                                ...            ...              ...
264830   Kettle Sweet Chilli And Sour          Cream            175.0
264831             Tostitos Splash Of           Lime            175.0
264832               Doritos Mexicana                           170.0
264833      Doritos Corn Chip Mexican       Jalapeno            150.0
264834             Tostitos Splash Of           Lime            175.0

        quantity  total_sales              lifestage customer_type
0              2          6.0   Young Singles/Couples       Premium
1              3          6.3  Midage Singles/Couples        Budget
2              2          2.9  Midage Singles/Couples        Budget
3              5         15.0  Midage Singles/Couples        Budget
4              3         13.8  Midage Singles/Couples        Budget
...          ...          ...                     ...           ...
264830         2         10.8   Young Singles/Couples       Premium
264831         1          4.4   Young Singles/Couples       Premium
264832         2          8.8   Young Singles/Couples       Premium
264833         2          7.8   Young Singles/Couples       Premium
264834         2          8.8   Young Singles/Couples       Premium

[264835 rows x 13 columns]>
```

```
merged_df.corr
```

```
<bound method DataFrame.corr of        transaction_date transaction_id customer_id store_number product_id  \
0            2018-10-17              1        1000            1          5
1            2019-05-14            348        1307            1         66
2            2019-05-20            383        1343            1         61
3            2018-08-17            974        2373            2         69
4            2018-08-18           1038        2426            2        108
...                 ...            ...         ...          ...        ...
264830       2018-11-12         270088      272319          272         89
264831       2019-03-09         270154      272358          272         74
264832       2018-08-13         270187      272379          272         51
264833       2018-11-06         270188      272379          272         42
264834       2018-12-27         270189      272380          272         74

                                    product_name  \
0         Natural Chip        Compny Seasalt175G
1                       Ccs Nacho Cheese    175G
2         Smiths Crinkle Cut  Chips Chicken 170G
3         Smiths Chip Thinly  S/Cream&Onion 175G
4       Kettle Tortilla Chpshny&Jlpno Chili 150G
...                                      ...
264830   Kettle Sweet Chilli And Sour Cream 175G
264831             Tostitos Splash Of  Lime 175G
264832                  Doritos Mexicana    170G
264833   Doritos Corn Chip Mexican Jalapeno 150G
264834             Tostitos Splash Of  Lime 175G

                               brand        flavour  pack_size_grams  \
0                       Natural Chip         Compny            175.0
1                    Ccs Nacho Cheese                           175.0
2          Smiths Crinkle Cut  Chips        Chicken            170.0
3                  Smiths Chip Thinly  S/Cream&Onion            175.0
4       Kettle Tortilla Chpshny&Jlpno          Chili            150.0
...                                ...            ...              ...
264830   Kettle Sweet Chilli And Sour          Cream            175.0
```

```
264831             Tostitos Splash Of           Lime            175.0
264832               Doritos Mexicana                           170.0
264833      Doritos Corn Chip Mexican       Jalapeno            150.0
264834             Tostitos Splash Of           Lime            175.0

        quantity  total_sales              lifestage customer_type
0              2          6.0   Young Singles/Couples      Premium
1              3          6.3  Midage Singles/Couples       Budget
2              2          2.9  Midage Singles/Couples       Budget
3              5         15.0  Midage Singles/Couples       Budget
4              3         13.8  Midage Singles/Couples       Budget
...          ...          ...                     ...          ...
264830         2         10.8   Young Singles/Couples      Premium
264831         1          4.4   Young Singles/Couples      Premium
264832         2          8.8   Young Singles/Couples      Premium
264833         2          7.8   Young Singles/Couples      Premium
264834         2          8.8   Young Singles/Couples      Premium

[264835 rows x 13 columns]>
```

```
merged_df.count()
```

```
transaction_date    264835
transaction_id      264835
customer_id         264835
store_number        264835
product_id          264835
product_name        264835
brand               264835
flavour             264835
pack_size_grams     264835
quantity            264835
total_sales         264835
lifestage           264835
customer_type       264835
dtype: int64
```

## 1. Customer Segmentation Analysis

### Objective:

Analyze customer behavior across segments defined by:

- **Lifestage**
- **Customer_type**

### Key Metrics to Evaluate:

1. **Total Spend**
   - Total monetary value of purchases
2. **Purchase Volume**
   - Total quantity of items purchased
3. **Average Basket Size**
   - Average transaction value
4. **Transaction Frequency**
   - Frequency of purchases over time

```
merged_df.columns
```

```
Index(['transaction_date', 'transaction_id', 'customer_id', 'store_number',
       'product_id', 'product_name', 'brand', 'flavour', 'pack_size_grams',
       'quantity', 'total_sales', 'lifestage', 'customer_type'],
      dtype='object')
```

```
merged_df['customer_type'].unique()
```

```
array(['Premium', 'Budget', 'Mainstream'], dtype=object)
```

```
merged_df['lifestage'].unique()
```

```
array(['Young Singles/Couples', 'Midage Singles/Couples', 'New Families',
       'Older Families', 'Older Singles/Couples', 'Retirees',
       'Young Families'], dtype=object)
```

```
# Jupyter optimized version
customer_segment_metrics = merged_df.groupby(['lifestage', 'customer_type']).agg(
    total_sales=('total_sales', 'sum'),
    total_quantity=('quantity', 'sum'),
    num_transactions=('transaction_id', 'nunique'),
    unique_customers=('customer_id', 'nunique')
).reset_index()

# Calculate derived metrics
customer_segment_metrics['avg_sales_per_txn'] = (customer_segment_metrics['total_sales'] / customer_segment_metrics['num_transactions']).rou
customer_segment_metrics['avg_quantity_per_txn'] = (customer_segment_metrics['total_quantity'] / customer_segment_metrics['num_transactions'

# Display with formatting
from IPython.display import display

display(
    customer_segment_metrics.sort_values('total_sales', ascending=False).head(10).style.format({
        'total_sales': '${:,.2f}',
        'avg_sales_per_txn': '${:,.2f}',
        'total_quantity': '{:,.0f}',
        'avg_quantity_per_txn': '{:,.2f}',
        'num_transactions': '{:,.0f}',
        'unique_customers': '{:,.0f}'
    })
)
```

| | lifestage | customer_type | total_sales | total_quantity | num_transactions | unique_customers | avg_sales_per_txn | avg_quantity_per_txn |
|---|---|---|---|---|---|---|---|---|
| **6** | Older Families | Budget | $168,363.25 | 45,065 | 22,935 | 4,675 | $7.34 | 1.96 |
| **19** | Young Singles/Couples | Mainstream | $157,621.60 | 38,632 | 20,783 | 8,088 | $7.58 | 1.86 |
| **13** | Retirees | Mainstream | $155,677.05 | 40,518 | 21,363 | 6,479 | $7.29 | 1.90 |
| **15** | Young Families | Budget | $139,345.85 | 37,111 | 18,970 | 4,017 | $7.35 | 1.96 |
| **9** | Older Singles/Couples | Budget | $136,769.80 | 35,220 | 18,301 | 4,929 | $7.47 | 1.92 |
| **10** | Older Singles/Couples | Mainstream | $133,393.80 | 34,997 | 18,194 | 4,930 | $7.33 | 1.92 |
| **11** | Older Singles/Couples | Premium | $132,257.15 | 33,984 | 17,654 | 4,750 | $7.49 | 1.93 |
| **12** | Retirees | Budget | $113,147.80 | 28,764 | 15,113 | 4,454 | $7.49 | 1.90 |
| **7** | Older Families | Mainstream | $103,445.55 | 27,756 | 14,113 | 2,831 | $7.33 | 1.97 |
| **14** | Retirees | Premium | $97,646.05 | 24,884 | 13,036 | 3,872 | $7.49 | 1.91 |

```
# GOAL: Analyze spending patterns across all customer segments,
#       with metrics sorted by highest spenders first

# 1. SETUP COMPLETE COMBINATIONS
# ------------------------------
# Get all possible lifestage + customer_type pairs
all_combinations = pd.MultiIndex.from_product(
    [merged_df['lifestage'].unique(),
     merged_df['customer_type'].unique()],
    names=['lifestage', 'customer_type']
).to_frame(index=False)

# 2. CALCULATE METRICS
# --------------------
# Raw numbers first (no formatting yet)
metrics = all_combinations.merge(
    merged_df.groupby(['lifestage', 'customer_type']).agg(
        total_sales=('total_sales', 'sum'),
        total_quantity=('quantity', 'sum'),
        num_transactions=('transaction_id', 'nunique'),
        unique_customers=('customer_id', 'nunique')
    ).reset_index(),
    how='left'
).fillna(0)  # Show zeros for missing combinations

# 3. DERIVED METRICS
# ------------------
# With protection against empty segments
metrics['avg_sales_per_txn'] = np.where(
    metrics['num_transactions'] > 0,
    metrics['total_sales'] / metrics['num_transactions'],
    0
```

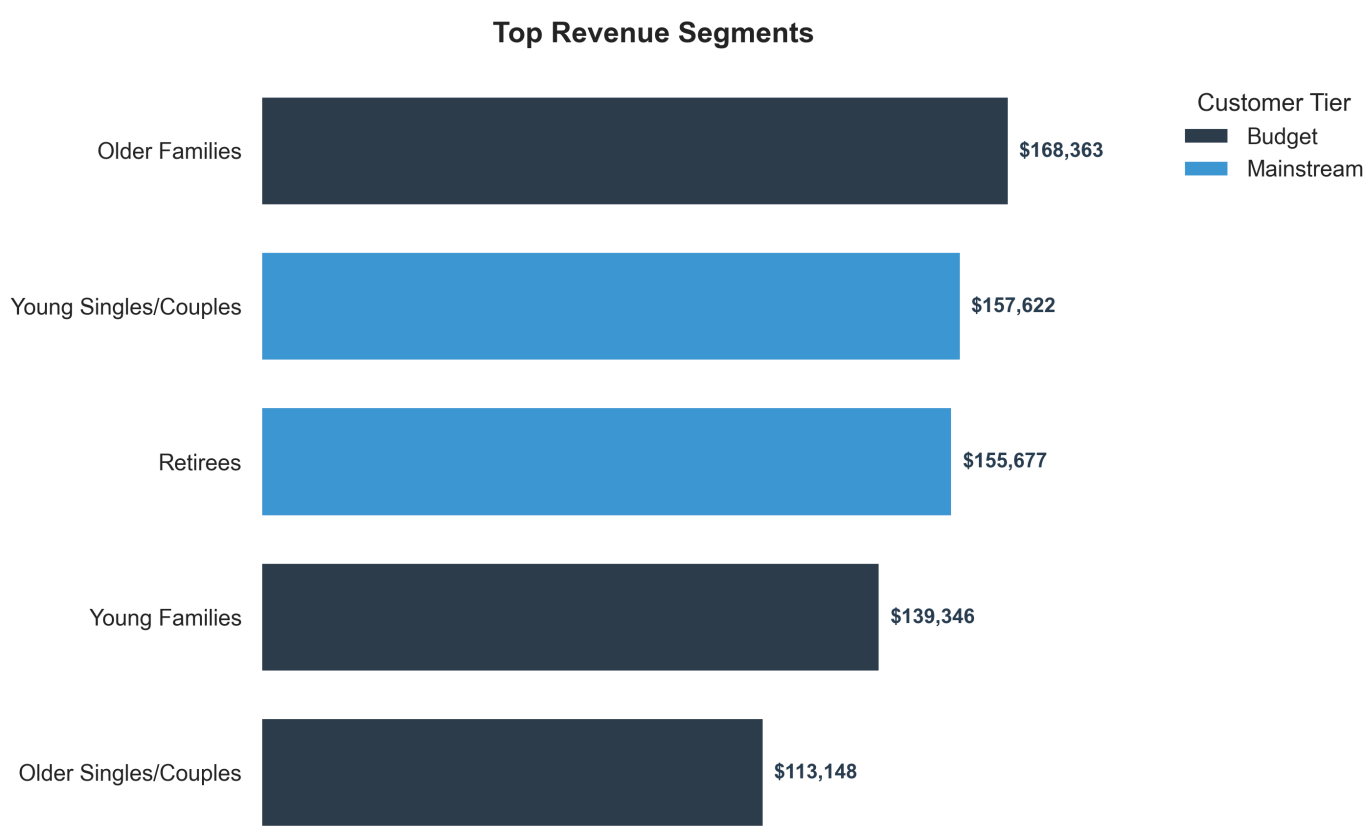
```
).round(2)

metrics['avg_quantity_per_txn'] = np.where(
    metrics['num_transactions'] > 0,
    metrics['total_quantity'] / metrics['num_transactions'],
    0
).round(2)

# 4. SORTING & FORMATTING
# -----------------------
# Sort by total_sales (highest to lowest)
final_output = (metrics
    .sort_values('total_sales', ascending=False)
    .style
    .format({
        'total_sales': '${:,.2f}',
        'avg_sales_per_txn': '${:,.2f}',
        'total_quantity': '{:,.0f}',
        'num_transactions': '{:,.0f}',
        'unique_customers': '{:,.0f}',
        'avg_quantity_per_txn': '{:,.2f}'
    })
    .set_caption("TOP PERFORMING SEGMENTS")
    .set_properties(**{'text-align': 'center'})
)

# 5. DISPLAY RESULTS
# ------------------
final_output
```

TOP PERFORMING SEGMENTS

| | lifestage | customer_type | total_sales | total_quantity | num_transactions | unique_customers | avg_sales_per_txn | avg_quantity_per_txn |
|---|---|---|---|---|---|---|---|---|
| **10** | Older Families | Budget | $168,363.25 | 45,065 | 22,935 | 4,675 | $7.34 | 1.96 |
| **2** | Young Singles/Couples | Mainstream | $157,621.60 | 38,632 | 20,783 | 8,088 | $7.58 | 1.86 |
| **17** | Retirees | Mainstream | $155,677.05 | 40,518 | 21,363 | 6,479 | $7.29 | 1.90 |
| **19** | Young Families | Budget | $139,345.85 | 37,111 | 18,970 | 4,017 | $7.35 | 1.96 |
| **13** | Older Singles/Couples | Budget | $136,769.80 | 35,220 | 18,301 | 4,929 | $7.47 | 1.92 |
| **14** | Older Singles/Couples | Mainstream | $133,393.80 | 34,997 | 18,194 | 4,930 | $7.33 | 1.92 |
| **12** | Older Singles/Couples | Premium | $132,257.15 | 33,984 | 17,654 | 4,750 | $7.49 | 1.93 |
| **16** | Retirees | Budget | $113,147.80 | 28,764 | 15,113 | 4,454 | $7.49 | 1.90 |
| **11** | Older Families | Mainstream | $103,445.55 | 27,756 | 14,113 | 2,831 | $7.33 | 1.97 |
| **15** | Retirees | Premium | $97,646.05 | 24,884 | 13,036 | 3,872 | $7.49 | 1.91 |
| **20** | Young Families | Mainstream | $92,788.75 | 25,044 | 12,808 | 2,728 | $7.24 | 1.96 |
| **5** | Midage Singles/Couples | Mainstream | $90,803.85 | 22,699 | 11,801 | 3,340 | $7.69 | 1.92 |
| **18** | Young Families | Premium | $84,025.50 | 22,406 | 11,464 | 2,433 | $7.33 | 1.95 |
| **9** | Older Families | Premium | $81,958.40 | 22,171 | 11,078 | 2,274 | $7.40 | 2.00 |
| **1** | Young Singles/Couples | Budget | $61,141.60 | 16,671 | 9,214 | 3,779 | $6.64 | 1.81 |
| **3** | Midage Singles/Couples | Premium | $58,432.65 | 15,526 | 8,160 | 2,431 | $7.16 | 1.90 |
| **0** | Young Singles/Couples | Premium | $41,642.10 | 11,331 | 6,258 | 2,574 | $6.65 | 1.81 |
| **4** | Midage Singles/Couples | Budget | $35,514.80 | 9,496 | 4,988 | 1,504 | $7.12 | 1.90 |
| **7** | New Families | Budget | $21,928.45 | 5,571 | 2,991 | 1,112 | $7.33 | 1.86 |
| **8** | New Families | Mainstream | $17,013.90 | 4,319 | 2,321 | 849 | $7.33 | 1.86 |
| **6** | New Families | Premium | $11,491.10 | 2,957 | 1,584 | 588 | $7.25 | 1.87 |

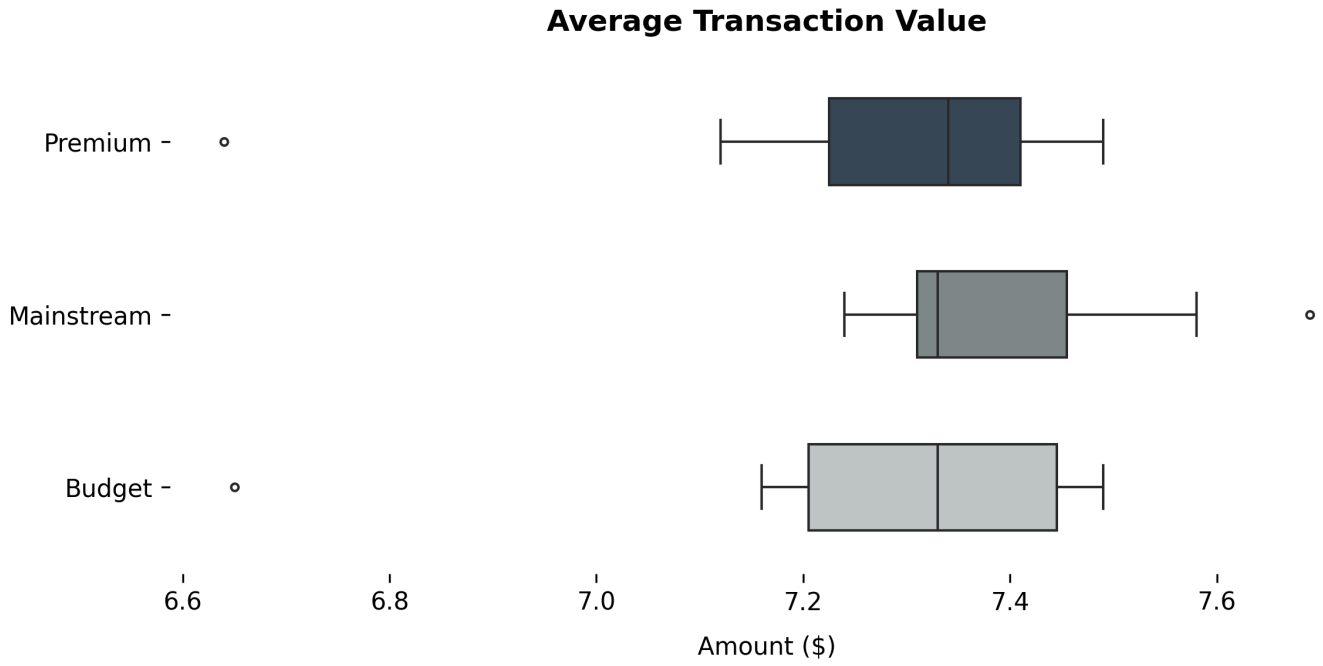
```
import matplotlib.pyplot as plt
import seaborn as sns
# Set professional style (updated for modern matplotlib)
plt.style.use('default')  # Reset to default first
sns.set_theme(style="whitegrid")  # This is the correct seaborn style name

# Create the figure with better proportions
plt.figure(figsize=(10, 6), dpi=300)

# Sample data - REPLACE THIS WITH YOUR ACTUAL metrics_sorted DataFrame
data = {
    'lifestage': ['Older Families', 'Young Singles/Couples', 'Retirees',
                  'Young Families', 'Older Singles/Couples'],
    'total_sales': [168363, 157622, 155677, 139346, 113148],
    'customer_type': ['Budget', 'Mainstream', 'Mainstream', 'Budget', 'Budget']
}
metrics_sorted = pd.DataFrame(data)

# Create the barplot with improved formatting
ax = sns.barplot(
```

```
    x='total_sales',
    y='lifestage',
    hue='customer_type',
    data=metrics_sorted,
    palette=['#2c3e50', '#3498db'],  # Reduced to 2 colors matching 2 customer types
    width=0.7,  # Optimal width
    saturation=0.9,
    dodge=False,
    err_kws={'linewidth': 0}  # Updated way to remove error bars
)

# Remove all spines and gridlines
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
ax.spines['left'].set_visible(False)
ax.spines['bottom'].set_visible(False)

# Remove gridlines
ax.grid(False)

# Remove x-axis
ax.set_xticks([])
ax.set_xlabel('')

# Customize labels and titles
plt.title('Top Revenue Segments', fontsize=14, pad=15, fontweight='bold')
plt.ylabel('')
plt.legend(title='Customer Tier', frameon=False, bbox_to_anchor=(1.15, 1))

# Format value labels
for container in ax.containers:
    ax.bar_label(container,
                 labels=[f'${x:,.0f}' for x in container.datavalues],  # Proper formatting
                 padding=5,
                 fontsize=10,
                 fontweight='bold',
                 color='#2c3e50')

# Adjust layout and save
plt.tight_layout()
plt.savefig('top_revenue_segments.png', bbox_inches='tight', dpi=300)
plt.show()
```

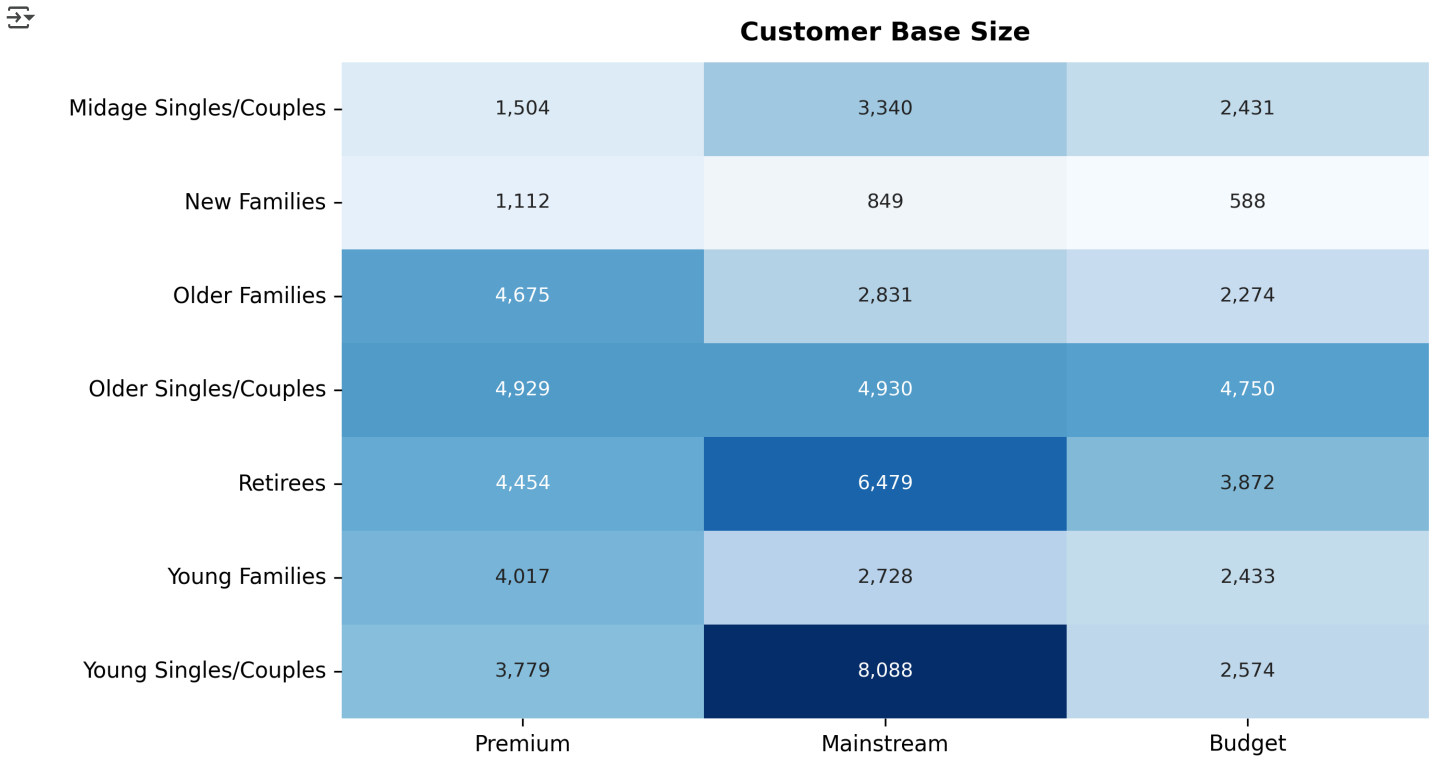



```
plt.figure(figsize=(8, 4), dpi=300)
ax = sns.boxplot(
    x='avg_sales_per_txn',
    y='customer_type',
    data=metrics_sorted,
    palette=['#34495e', '#7f8c8d', '#bdc3c7'],  # Monochromatic
    width=0.5,
    linewidth=1,
    fliersize=3
)

# Remove all spines and grids
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
ax.spines['left'].set_visible(False)
ax.spines['bottom'].set_visible(False)

# Clean annotations
plt.title('Average Transaction Value', fontsize=12, pad=10, fontweight='semibold')
plt.xlabel('Amount ($)', fontsize=10, labelpad=8)
plt.ylabel('')
ax.set_yticklabels(['Premium', 'Mainstream', 'Budget'], fontsize=10)

plt.tight_layout()
plt.savefig('basket_size_comparison.png', bbox_inches='tight', dpi=300)
plt.show()
```

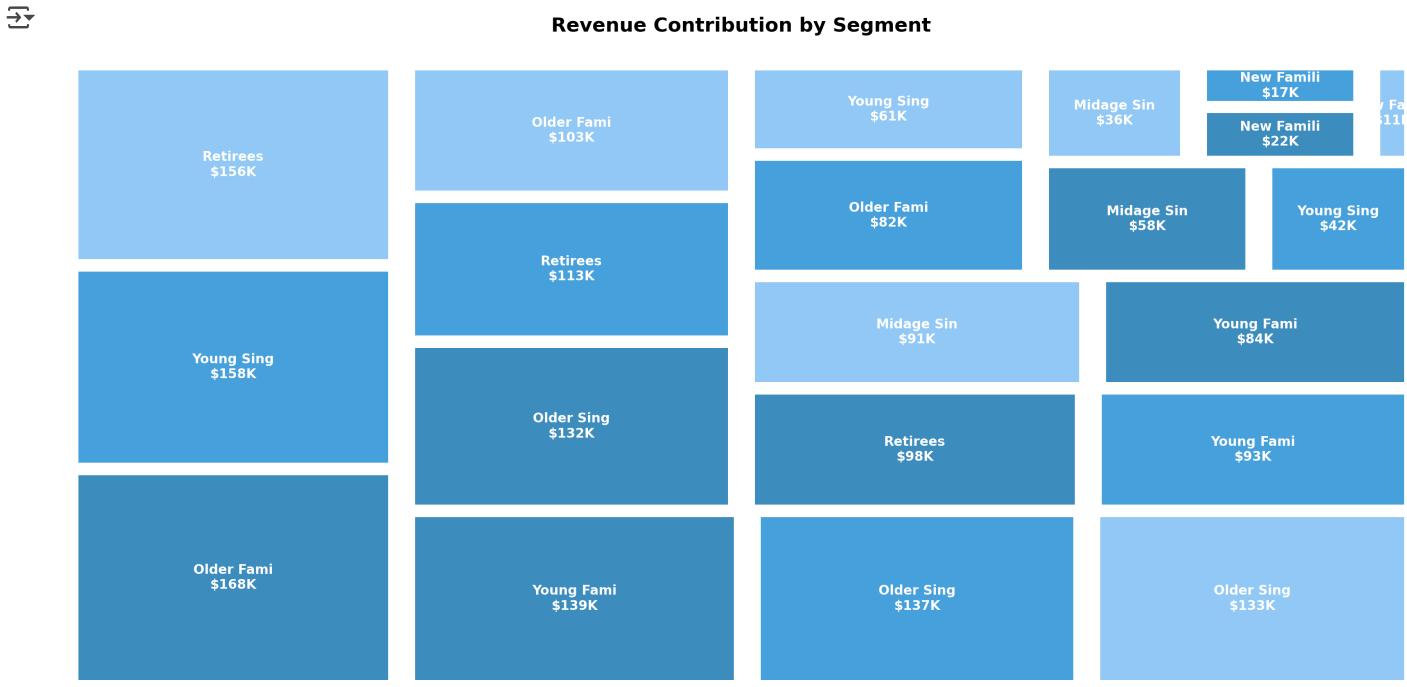
```
C:\Users\user\AppData\Local\Temp\ipykernel_21752\2051369605.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend

  ax = sns.boxplot(
C:\Users\user\AppData\Local\Temp\ipykernel_21752\2051369605.py:22: UserWarning: set_ticklabels() should only be used with a fixed number
  ax.set_yticklabels(['Premium', 'Mainstream', 'Budget'], fontsize=10)
```




```
plt.figure(figsize=(9, 5), dpi=300)
ax = sns.heatmap(
    pivot_data,
    annot=True,
    fmt=',.0f',
    cmap='Blues',
    linewidths=0,
    annot_kws={'size': 9},
    cbar=False
)

# Remove all spines
for spine in ['top', 'right', 'left', 'bottom']:
    ax.spines[spine].set_visible(False)

# Professional labels
plt.title('Customer Base Size', fontsize=12, pad=10, fontweight='semibold')
plt.xlabel('')
plt.ylabel('')
ax.set_xticklabels(['Premium', 'Mainstream', 'Budget'], fontsize=10)
ax.set_yticklabels(ax.get_yticklabels(), rotation=0, fontsize=10)

plt.tight_layout()
plt.savefig('customer_distribution.png', bbox_inches='tight', dpi=300)
plt.show()
```




```
plt.figure(figsize=(12, 6), dpi=300)
squarify.plot(
    sizes=metrics_sorted['total_sales'],
    label=[f"{row['lifestage'][:10]}\n${row['total_sales']/1000:.0f}K"
           for _, row in metrics_sorted.iterrows()],
    color=['#2980b9', '#3498db', '#89c4f4'],  # Blue gradient
    alpha=0.9,
    text_kwargs={'fontsize':8, 'color':'white', 'fontweight':'bold'},
    pad=1,
    bar_kwargs={'linewidth':0}  # No borders
)

# Remove all axes
plt.axis('off')
plt.title('Revenue Contribution by Segment', fontsize=12, pad=20, fontweight='semibold')

plt.tight_layout()
plt.savefig('revenue_treemap.png', bbox_inches='tight', dpi=300, transparent=True)
plt.show()
```




## KEY FINDINGS

### 🏆 Top Performers

- **Older Families (Budget)**: Highest revenue $(168K) despite moderate basket size (7.34)$
- **Young Singles (Mainstream)**: 2nd highest sales with largest customer base (8,088)
- **Retirees (Mainstream)**: Strong performance with high transaction volume (21,363)

### 💡 Notable Patterns

1. **Budget segments dominate** top 5 positions
2. **Mainstream** shows consistent performance across lifestages
3. **Premium underperforms** - appears in rankings only after #12

### 📊 Metric Benchmarks

- **Average basket size**: $7.00 - 7.50$ across most segments
- **Transactions/customer**: ~5 transactions per customer
- **Quantity per transaction**: Consistently ~2 items

## RECOMMENDATIONS

1. **Increase focus on Budget segments** - Driving majority of revenue
2. **Upsell Premium customers** - Current basket sizes match Budget tiers
3. **New Families development** - Lowest performing group needs attention

....

.....

## 2. Product-Level Insights

🎯 **Objective:**
Identify top-performing products and understand:

1. Revenue contribution

2. Sales volume
3. Purchase frequency
4. Customer reach

```
# Aggregating key product performance indicators
product_insights = merged_df.groupby('product_name').agg(
    total_sales=('total_sales', 'sum'),
    total_units_sold=('quantity', 'sum'),
    num_transactions=('transaction_id', 'nunique'),
    unique_customers=('customer_id', 'nunique')
).reset_index()

# Calculating derived metric
product_insights['avg_sales_per_transaction'] = (
    product_insights['total_sales'] / product_insights['num_transactions']
).round(2)

# Sorting by total revenue
product_insights = product_insights.sort_values(by='total_sales', ascending=False)
```


```
# Aggregating key product performance indicators
product_insights = merged_df.groupby('product_name').agg(
    total_sales=('total_sales', 'sum'),
    total_units_sold=('quantity', 'sum'),
    num_transactions=('transaction_id', 'nunique'),
    unique_customers=('customer_id', 'nunique')
).reset_index()

# Calculating derived metric
product_insights['avg_sales_per_transaction'] = (
    product_insights['total_sales'] / product_insights['num_transactions']
).round(2)

# Sorting by total revenue
product_insights = product_insights.sort_values(by='total_sales', ascending=False)
```


```
print(product_insights.head(10))
```

```
                              product_name  total_sales  total_units_sold  \
11          Dorito Corn Chp     Supreme 380G      40352.0              6509
86    Smiths Crnkle Chip  Orgnl Big Bag 380G      36367.6              6164
77  Smiths Crinkle Chips Salt & Vinegar 330G      34804.2              6106
33    Kettle Mozzarella   Basil & Pesto 175G      34457.4              6381
76         Smiths Crinkle      Original 330G      34302.6              6018
6                       Cheezels Cheese 330G      34296.9              6017
12          Doritos Cheese      Supreme 330G      33390.6              5858
39   Kettle Sweet Chilli And Sour Cream 175G      33031.8              6120
34                     Kettle Original 175G      32740.2              6064
35      Kettle Sea Salt     And Vinegar 175G      32589.0              6035

    num_transactions  unique_customers  avg_sales_per_transaction
11              3185              3112                      12.67
86              3233              3149                      11.25
77              3197              3106                      10.89
33              3304              3215                      10.43
76              3142              3064                      10.92
6               3149              3061                      10.89
12              3052              2991                      10.94
39              3200              3103                      10.32
34              3159              3081                      10.36
35              3173              3084                      10.27
```

```
# 📦 Product-Level Insights

# Grouping by product name to analyze performance
# Aggregating key metrics: total sales, quantity sold, transactions, and unique buyers
product_insights = merged_df.groupby('product_name').agg(
    total_sales=('total_sales', 'sum'),
    total_units_sold=('quantity', 'sum'),
    num_transactions=('transaction_id', 'nunique'),
    unique_customers=('customer_id', 'nunique')
).reset_index()
```

```
# Calculating average sales per transaction to evaluate product value perception
product_insights['avg_sales_per_transaction'] = (
    product_insights['total_sales'] / product_insights['num_transactions']
).round(2)

# Sorting by total sales to identify top-performing SKUs
product_insights = product_insights.sort_values(by='total_sales', ascending=False)

# Formatting: add $ sign and comma separators for better readability
product_insights['total_sales'] = product_insights['total_sales'].apply(lambda x: f"${x:,.2f}")
product_insights['avg_sales_per_transaction'] = product_insights['avg_sales_per_transaction'].apply(lambda x: f"${x:,.2f}")
product_insights['total_units_sold'] = product_insights['total_units_sold'].apply(lambda x: f"{x:,}")
product_insights['num_transactions'] = product_insights['num_transactions'].apply(lambda x: f"{x:,}")
product_insights['unique_customers'] = product_insights['unique_customers'].apply(lambda x: f"{x:,}")

# Previewing the top 10 best-selling products
product_insights.head(10)
```

| | product_name | total_sales | total_units_sold | num_transactions | unique_customers | avg_sales_per_transaction |
|---|---|---|---|---|---|---|
| **11** | Dorito Corn Chp Supreme 380G | $40,352.00 | 6,509 | 3,185 | 3,112 | $12.67 |
| **86** | Smiths Crnkle Chip Orgnl Big Bag 380G | $36,367.60 | 6,164 | 3,233 | 3,149 | $11.25 |
| **77** | Smiths Crinkle Chips Salt & Vinegar 330G | $34,804.20 | 6,106 | 3,197 | 3,106 | $10.89 |
| **33** | Kettle Mozzarella Basil & Pesto 175G | $34,457.40 | 6,381 | 3,304 | 3,215 | $10.43 |
| **76** | Smiths Crinkle Original 330G | $34,302.60 | 6,018 | 3,142 | 3,064 | $10.92 |
| **6** | Cheezels Cheese 330G | $34,296.90 | 6,017 | 3,149 | 3,061 | $10.89 |
| **12** | Doritos Cheese Supreme 330G | $33,390.60 | 5,858 | 3,052 | 2,991 | $10.94 |
| **39** | Kettle Sweet Chilli And Sour Cream 175G | $33,031.80 | 6,120 | 3,200 | 3,103 | $10.32 |
| **34** | Kettle Original 175G | $32,740.20 | 6,064 | 3,159 | 3,081 | $10.36 |
| **35** | Kettle Sea Salt And Vinegar 175G | $32,589.00 | 6,035 | 3,173 | 3,084 | $10.27 |

```
# 🧮 Grouping by product, lifestage, and customer_type
product_segmentation_summary = merged_df.groupby(
    ['product_name', 'lifestage', 'customer_type']
).agg(
    total_sales_raw=('total_sales', 'sum'),  # preserve raw numeric for sorting
    total_quantity=('quantity', 'sum'),
    num_transactions=('transaction_id', 'nunique'),
    unique_customers=('customer_id', 'nunique')
).reset_index()

# 🎯 Calculating KPIs
product_segmentation_summary['avg_sales_per_txn'] = (
    product_segmentation_summary['total_sales_raw'] / product_segmentation_summary['num_transactions']
)
product_segmentation_summary['avg_quantity_per_txn'] = (
    product_segmentation_summary['total_quantity'] / product_segmentation_summary['num_transactions']
)

# 🔽 Sorting by total_sales in descending order
product_segmentation_summary = product_segmentation_summary.sort_values(
    by='total_sales_raw', ascending=False
)

# 💲 Formatting for presentation
product_segmentation_summary['total_sales'] = product_segmentation_summary['total_sales_raw'].apply(lambda x: f"${x:,.2f}")
product_segmentation_summary['total_quantity'] = product_segmentation_summary['total_quantity'].apply(lambda x: f"{x:,}")
product_segmentation_summary['num_transactions'] = product_segmentation_summary['num_transactions'].apply(lambda x: f"{x:,}")
product_segmentation_summary['unique_customers'] = product_segmentation_summary['unique_customers'].apply(lambda x: f"{x:,}")
product_segmentation_summary['avg_sales_per_txn'] = product_segmentation_summary['avg_sales_per_txn'].apply(lambda x: f"${x:.2f}")
product_segmentation_summary['avg_quantity_per_txn'] = product_segmentation_summary['avg_quantity_per_txn'].apply(lambda x: f"{x:.2f}")

# 🧹 Drop raw column used for sorting
product_segmentation_summary.drop(columns='total_sales_raw', inplace=True)

# 📌 Preview top 10 sorted rows
product_segmentation_summary.head(10)
```

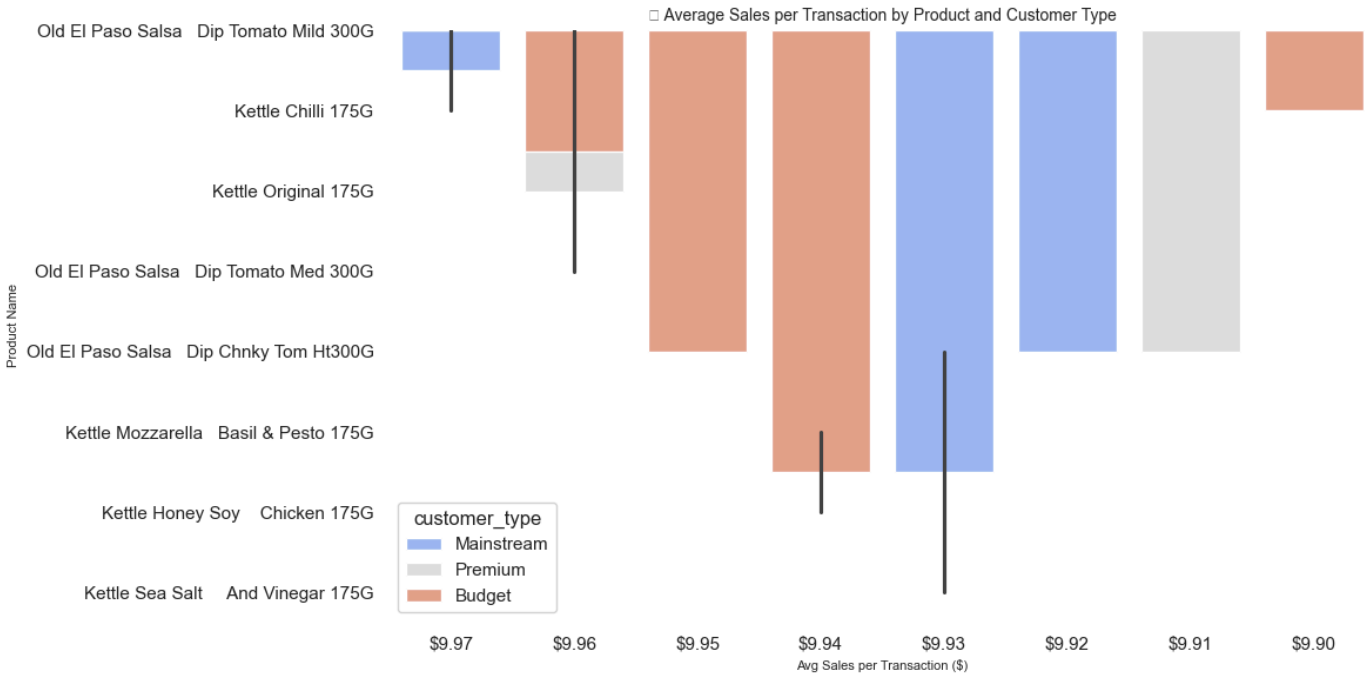
| | product_name | lifestage | customer_type | total_quantity | num_transactions | unique_customers | avg_sales_per_txn | avg_quantity_pe |
|---|---|---|---|---|---|---|---|---|
| **250** | Dorito Corn Chp Supreme 380G | Young Singles/Couples | Mainstream | 569 | 303 | 296 | $12.08 | |
| **1825** | Smiths Crnkle Chip Orgnl Big Bag 380G | Young Singles/Couples | Mainstream | 596 | 323 | 318 | $10.89 | |
| **712** | Kettle Mozzarella Basil & Pesto 175G | Young Singles/Couples | Mainstream | 626 | 332 | 325 | $10.18 | |
| **1636** | Smiths Crinkle Chips Salt & Vinegar 330G | Young Singles/Couples | Mainstream | 582 | 314 | 310 | $10.56 | |
| **271** | Doritos Cheese Supreme 330G | Young Singles/Couples | Mainstream | 559 | 303 | 299 | $10.52 | |
| **1623** | Smiths Crinkle Chips Salt & Vinegar 330G | Older Families | Budget | 559 | 289 | 278 | $11.03 | |
| **237** | Dorito Corn Chp Supreme 380G | Older Families | Budget | 486 | 248 | 242 | $12.59 | |
| **132** | Cheezels Cheese 330G | Older Families | Budget | 543 | 275 | 268 | $11.25 | |
| **145** | Cheezels Cheese 330G | Young Singles/Couples | Mainstream | 542 | 287 | 280 | $10.76 | |
| **838** | Kettle Sweet Chilli And Sour Cream 175G | Young Singles/Couples | Mainstream | 572 | 306 | 299 | $10.09 | |

```
# 🔁 Converting total_sales back to numeric for plotting
product_segmentation_summary['total_sales_numeric'] = (
    product_segmentation_summary['total_sales']
    .replace('[\$,]', '', regex=True)
    .astype(float)
)

# 🎨 Set visual style
plt.figure(figsize=(10, 6))
pivot_table = product_segmentation_summary.pivot_table(
    index='lifestage',
    columns='customer_type',
    values='total_sales_numeric',
    aggfunc='sum'
)

sns.heatmap(pivot_table, annot=True, fmt=".0f", cmap="YlGnBu", cbar_kws={'label': 'Total Sales ($)'})
plt.title("💰 Total Product Sales by Lifestage and Customer Type", fontsize=10)
plt.xlabel("Customer Type", fontsize=8)
plt.ylabel("Lifestage", fontsize=8)

# ✨ Professional formatting
plt.grid(False)
for spine in plt.gca().spines.values():
    spine.set_visible(False)

plt.tight_layout()
plt.savefig('product_sales_heatmap.png', bbox_inches='tight', dpi=300)
plt.show()
```

```
<>:4: SyntaxWarning: invalid escape sequence '\$'
<>:4: SyntaxWarning: invalid escape sequence '\$'
C:\Users\user\AppData\Local\Temp\ipykernel_21752\2504434748.py:4: SyntaxWarning: invalid escape sequence '\$'
  .replace('[\$,]', '', regex=True)
C:\Users\user\AppData\Local\Temp\ipykernel_21752\2504434748.py:27: UserWarning: Glyph 128176 (\N{MONEY BAG}) missing from font(s) Arial.
  plt.tight_layout()
C:\Users\user\AppData\Local\Temp\ipykernel_21752\2504434748.py:28: UserWarning: Glyph 128176 (\N{MONEY BAG}) missing from font(s) Arial.
  plt.savefig('product_sales_heatmap.png', bbox_inches='tight', dpi=300)
C:\Users\user\AppData\Roaming\Python\Python313\site-packages\IPython\core\pylabtools.py:170: UserWarning: Glyph 128176 (\N{MONEY BAG}) m
  fig.canvas.print_figure(bytes_io, **kw)
```

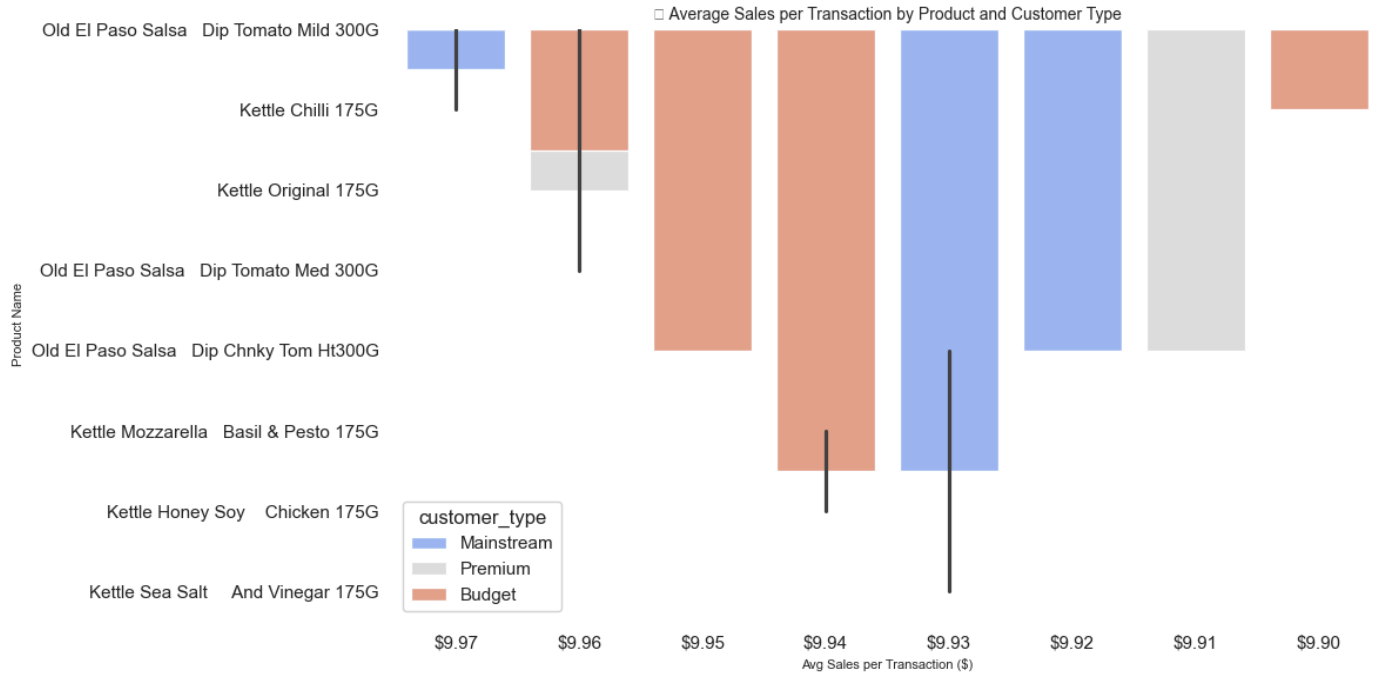

```
# 📊 Bar chart for avg sales per txn
plt.figure(figsize=(12, 6))
sns.barplot(
    data=product_segmentation_summary.sort_values('avg_sales_per_txn', ascending=False).head(15),
    x='avg_sales_per_txn',
    y='product_name',
    hue='customer_type',
    dodge=False,
    palette='coolwarm'
)
plt.title("🛒 Average Sales per Transaction by Product and Customer Type", fontsize=10)
plt.xlabel("Avg Sales per Transaction ($)", fontsize=8)
plt.ylabel("Product Name", fontsize=8)

# 🧹 Clean up
plt.grid(False)
for spine in plt.gca().spines.values():
    spine.set_visible(False)

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

```
C:\Users\user\AppData\Local\Temp\ipykernel_21752\2824794866.py:20: UserWarning: Glyph 128722 (\N{SHOPPING TROLLEY}) missing from font(s)
  plt.tight_layout()
C:\Users\user\AppData\Roaming\Python\Python313\site-packages\IPython\core\pylabtools.py:170: UserWarning: Glyph 128722 (\N{SHOPPING TROL
  fig.canvas.print_figure(bytes_io, **kw)
```




```
# 📊 Bar chart for avg sales per txn
plt.figure(figsize=(12, 6))
sns.barplot(
    data=product_segmentation_summary.sort_values('avg_sales_per_txn', ascending=False).head(15),
    x='avg_sales_per_txn',
    y='product_name',
    hue='customer_type',
    dodge=False,
    palette='coolwarm'
)
plt.title("🛒 Average Sales per Transaction by Product and Customer Type", fontsize=10)
plt.xlabel("Avg Sales per Transaction ($)", fontsize=8)
plt.ylabel("Product Name", fontsize=8)

# 🧹 Clean up
plt.grid(False)
for spine in plt.gca().spines.values():
    spine.set_visible(False)

plt.tight_layout()
plt.savefig('avg_sales_per_txn_by_product.png', bbox_inches='tight', dpi=300)
plt.show()
```

```
C:\Users\user\AppData\Local\Temp\ipykernel_21752\3269926872.py:20: UserWarning: Glyph 128722 (\N{SHOPPING TROLLEY}) missing from font(s)
  plt.tight_layout()
C:\Users\user\AppData\Local\Temp\ipykernel_21752\3269926872.py:21: UserWarning: Glyph 128722 (\N{SHOPPING TROLLEY}) missing from font(s)
  plt.savefig('avg_sales_per_txn_by_product.png', bbox_inches='tight', dpi=300)
C:\Users\user\AppData\Roaming\Python\Python313\site-packages\IPython\core\pylabtools.py:170: UserWarning: Glyph 128722 (\N{SHOPPING TROL
  fig.canvas.print_figure(bytes_io, **kw)
```




## Sales Performance Summary

### Top 5 Products by Revenue

1. **Dorito Corn Chp Supreme 380G** – **$40,352.00**
2. **Smiths Crnkle Chip Orgnl Big Bag 380G** – **$36,367.60**
3. **Smiths Crinkle Chips Salt & Vinegar 330G** – **$34,804.20**
4. **Kettle Mozzarella Basil & Pesto 175G** – **$34,457.40**
5. **Smiths Crinkle Original 330G** – **$34,302.60**

### Key Insights

- 🏆 **Dorito Corn Chp Supreme 380G** is the best-selling product in both **revenue ($40K+)** and **units sold (6,509)**.
- 🔁 **Kettle Mozzarella Basil & Pesto 175G** has the most **transactions (3,304)** and **unique customers (3,215)**.
- 📦 **Cheezels Cheese 330G** sells in high volume (6,017 units) but ranks **6th in revenue**.
- 💰 **Average transaction value** ranges from **$10.27 (Kettle Sea Salt & Vinegar)** to **$12.67 (Dorito Supreme)**.

### Recommendations

✅ **Push high-value products** (e.g., Dorito Supreme) with promotions to maximize revenue.
✅ **Stock more high-demand items** like Kettle Mozzarella and Smiths Crinkle chips.
✅ **Encourage repeat purchases** through loyalty programs for top-performing products.

.....

## Basket Size & Frequency Analysis

### Objectives

- **Quantify Customer Basket Size:**
  Measure the average number of items purchased per transaction to understand purchasing volume across different customer segments.
- **Evaluate Transaction Value:**
  Assess the average monetary value of each transaction, segmented by customer demographics, to identify high-value purchasing behavior.
- **Analyze Purchase Frequency:**
  Determine how often customers make transactions within the observed period, segmented by lifestyle and customer type, to uncover loyalty and engagement patterns.
- **Identify Segment-Specific Behaviors:**
  Highlight differences in basket size, transaction value, and purchase frequency among customer lifestage and type segments, supporting targeted marketing and promotional strategies.
- **Enable Strategic Recommendations:**
  Use these insights to inform data-driven strategies for upselling, cross-selling, and personalized customer engagement aimed at increasing revenue and customer retention.

```
# Group data by transaction to calculate basket size (quantity) and total sales per basket
basket_metrics = merged_df.groupby('transaction_id').agg(
    basket_size=('quantity', 'sum'),
    basket_value=('total_sales', 'sum'),
    customer_id=('customer_id', 'first')
).reset_index()

# Merge basket metrics with customer segmentation info
basket_metrics = basket_metrics.merge(
    merged_df[['customer_id', 'lifestage', 'customer_type']].drop_duplicates(),
    on='customer_id',
    how='left'
)

# Average basket size and value by segment
basket_summary = basket_metrics.groupby(['lifestage', 'customer_type']).agg(
    avg_basket_size=('basket_size', 'mean'),
    avg_basket_value=('basket_value', 'mean')
).reset_index()

# Calculate transaction frequency per customer
transaction_counts = merged_df.groupby('customer_id')['transaction_id'].nunique().reset_index()
transaction_counts.columns = ['customer_id', 'transaction_frequency']

# Merge frequency with segmentation data
transaction_freq = transaction_counts.merge(
    merged_df[['customer_id', 'lifestage', 'customer_type']].drop_duplicates(),
    on='customer_id',
    how='left'
)

# Average frequency by segment
frequency_summary = transaction_freq.groupby(['lifestage', 'customer_type']).agg(
    avg_transaction_frequency=('transaction_frequency', 'mean')
).reset_index()

# Display summaries
print("Basket Summary:\n", basket_summary)
print("\nTransaction Frequency Summary:\n", frequency_summary)
```

```
Basket Summary:
                  lifestage customer_type  avg_basket_size  avg_basket_value
0   Midage Singles/Couples        Budget         1.903769          7.120048
1   Midage Singles/Couples    Mainstream         1.923481          7.694589
2   Midage Singles/Couples       Premium         1.902696          7.160864
3            New Families        Budget         1.862588          7.331478
4            New Families    Mainstream         1.860836          7.330418
5            New Families       Premium         1.866793          7.254482
6          Older Families        Budget         1.964901          7.340887
7          Older Families    Mainstream         1.966697          7.329806
8          Older Families       Premium         2.001354          7.398303
9    Older Singles/Couples        Budget         1.924485          7.473351
10   Older Singles/Couples    Mainstream         1.923766          7.332527
11   Older Singles/Couples       Premium         1.924994          7.491669
```

```
12               Retirees        Budget         1.903262          7.486786
13               Retirees    Mainstream         1.896644          7.287228
14               Retirees       Premium         1.908868          7.490492
15         Young Families        Budget         1.956299          7.345590
16         Young Families    Mainstream         1.955340          7.244593
17         Young Families       Premium         1.954466          7.329510
18   Young Singles/Couples        Budget         1.809312          6.635728
19   Young Singles/Couples    Mainstream         1.858827          7.584160
20   Young Singles/Couples       Premium         1.810642          6.654219

Transaction Frequency Summary:
                  lifestage customer_type  avg_transaction_frequency
0   Midage Singles/Couples        Budget                   3.316489
1   Midage Singles/Couples    Mainstream                   3.533234
2   Midage Singles/Couples       Premium                   3.356643
3            New Families        Budget                   2.689748
4            New Families    Mainstream                   2.733804
5            New Families       Premium                   2.693878
6          Older Families        Budget                   4.905882
7          Older Families    Mainstream                   4.985164
8          Older Families       Premium                   4.871592
9    Older Singles/Couples        Budget                   3.712924
10   Older Singles/Couples    Mainstream                   3.690467
11   Older Singles/Couples       Premium                   3.716632
12               Retirees        Budget                   3.393130
13               Retirees    Mainstream                   3.297268
14               Retirees       Premium                   3.366736
15         Young Families        Budget                   4.722430
16         Young Families    Mainstream                   4.695015
17         Young Families       Premium                   4.711878
18   Young Singles/Couples        Budget                   2.438211
19   Young Singles/Couples    Mainstream                   2.569609
20   Young Singles/Couples       Premium                   2.431235
```

```
# Calculate basket size and value per transaction
basket_metrics = merged_df.groupby('transaction_id').agg(
    basket_size=('quantity', 'sum'),
    basket_value=('total_sales', 'sum'),
    customer_id=('customer_id', 'first')
).reset_index()

# Add customer segmentation info to basket metrics
basket_metrics = basket_metrics.merge(
    merged_df[['customer_id', 'lifestage', 'customer_type']].drop_duplicates(),
    on='customer_id',
    how='left'
)

# %%
# Calculate average basket metrics by customer segment
basket_summary = basket_metrics.groupby(['lifestage', 'customer_type']).agg(
    avg_basket_size=('basket_size', 'mean'),
    avg_basket_value=('basket_value', 'mean')
).reset_index()

# Display basket summary with formatting
from IPython.display import display
import pandas as pd

print("🛒 Basket Metrics by Customer Segment:")
display(basket_summary.style
        .format({'avg_basket_size': '{:.1f}', 'avg_basket_value': '${:,.2f}'})
        .set_caption("Average Basket Size and Value by Customer Segment")
        .background_gradient(cmap='Blues'))

# %%
# Calculate transaction frequency per customer
transaction_counts = merged_df.groupby('customer_id')['transaction_id'].nunique().reset_index()
transaction_counts.columns = ['customer_id', 'transaction_frequency']

# Add segmentation data to frequency metrics
transaction_freq = transaction_counts.merge(
    merged_df[['customer_id', 'lifestage', 'customer_type']].drop_duplicates(),
    on='customer_id',
    how='left'
)

# %%
# Calculate average transaction frequency by segment
```

```
frequency_summary = transaction_freq.groupby(['lifestage', 'customer_type']).agg(
    avg_transaction_frequency=('transaction_frequency', 'mean')
).reset_index()

# Display frequency summary with formatting
print("\n📊 Transaction Frequency by Customer Segment:")
display(frequency_summary.style
        .format({'avg_transaction_frequency': '{:.1f}'})
        .set_caption("Average Transaction Frequency by Customer Segment")
        .background_gradient(cmap='Greens'))
```

```
🛒 Basket Metrics by Customer Segment:
```

Average Basket Size and Value by Customer Segment

| | lifestage | customer_type | avg_basket_size | avg_basket_value |
|---|---|---|---|---|
| 0 | Midage Singles/Couples | Budget | 1.9 | $7.12 |
| 1 | Midage Singles/Couples | Mainstream | 1.9 | $7.69 |
| 2 | Midage Singles/Couples | Premium | 1.9 | $7.16 |
| 3 | New Families | Budget | 1.9 | $7.33 |
| 4 | New Families | Mainstream | 1.9 | $7.33 |
| 5 | New Families | Premium | 1.9 | $7.25 |
| 6 | Older Families | Budget | 2.0 | $7.34 |
| 7 | Older Families | Mainstream | 2.0 | $7.33 |
| 8 | Older Families | Premium | 2.0 | $7.40 |
| 9 | Older Singles/Couples | Budget | 1.9 | $7.47 |
| 10 | Older Singles/Couples | Mainstream | 1.9 | $7.33 |
| 11 | Older Singles/Couples | Premium | 1.9 | $7.49 |
| 12 | Retirees | Budget | 1.9 | $7.49 |
| 13 | Retirees | Mainstream | 1.9 | $7.29 |
| 14 | Retirees | Premium | 1.9 | $7.49 |
| 15 | Young Families | Budget | 2.0 | $7.35 |
| 16 | Young Families | Mainstream | 2.0 | $7.24 |
| 17 | Young Families | Premium | 2.0 | $7.33 |
| 18 | Young Singles/Couples | Budget | 1.8 | $6.64 |
| 19 | Young Singles/Couples | Mainstream | 1.9 | $7.58 |
| 20 | Young Singles/Couples | Premium | 1.8 | $6.65 |

```
📊 Transaction Frequency by Customer Segment:
```

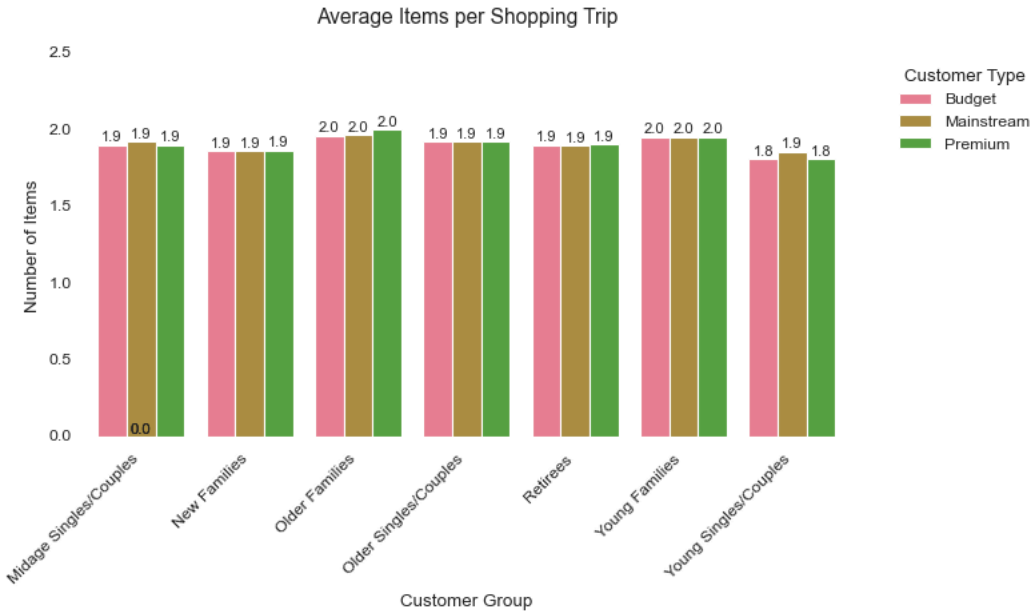
Average Transaction Frequency by Customer Segment

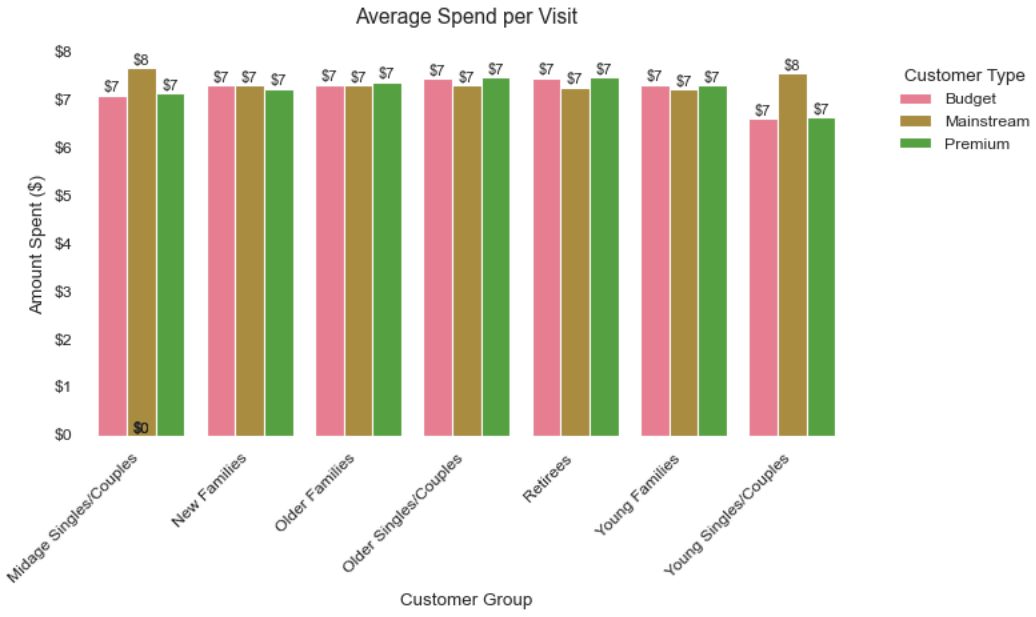
| | lifestage | customer_type | avg_transaction_frequency |
|---|---|---|---|
| 0 | Midage Singles/Couples | Budget | 3.3 |
| 1 | Midage Singles/Couples | Mainstream | 3.5 |
| 2 | Midage Singles/Couples | Premium | 3.4 |
| 3 | New Families | Budget | 2.7 |
| 4 | New Families | Mainstream | 2.7 |
| 5 | New Families | Premium | 2.7 |
| 6 | Older Families | Budget | 4.9 |
| 7 | Older Families | Mainstream | 5.0 |
| 8 | Older Families | Premium | 4.9 |
| 9 | Older Singles/Couples | Budget | 3.7 |
| 10 | Older Singles/Couples | Mainstream | 3.7 |
| 11 | Older Singles/Couples | Premium | 3.7 |
| 12 | Retirees | Budget | 3.4 |
| 13 | Retirees | Mainstream | 3.3 |
| 14 | Retirees | Premium | 3.4 |
| 15 | Young Families | Budget | 4.7 |
| 16 | Young Families | Mainstream | 4.7 |
| 17 | Young Families | Premium | 4.7 |
| 18 | Young Singles/Couples | Budget | 2.4 |
| 19 | Young Singles/Couples | Mainstream | 2.6 |
| 20 | Young Singles/Couples | Premium | 2.4 |

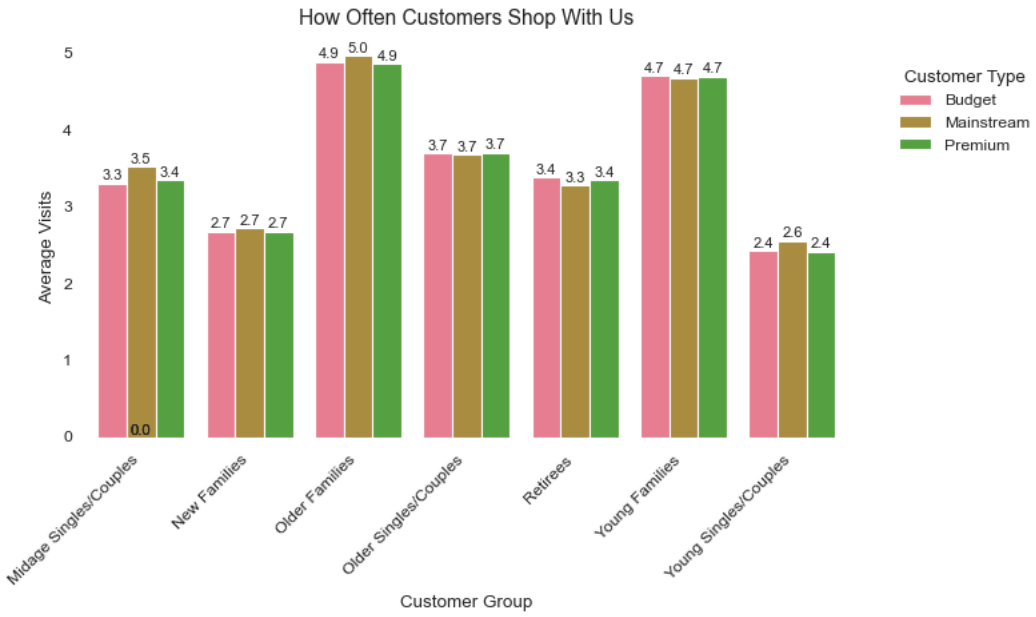
```
plt.style.use('classic')
sns.set_theme(style="white", palette="husl")

# First let's understand what customers are putting in their carts
customer_baskets = merged_df.groupby('transaction_id').agg(
    item_count=('quantity', 'sum'),
    total_spend=('total_sales', 'sum'),
    customer_id=('customer_id', 'first')
).reset_index()
```

```
# Add customer demographic information
customer_baskets = customer_baskets.merge(
    merged_df[['customer_id', 'lifestage', 'customer_type']].drop_duplicates(),
    on='customer_id',
    how='left'
)

# Calculate average basket metrics
basket_stats = customer_baskets.groupby(['lifestage', 'customer_type']).agg(
    avg_items=('item_count', 'mean'),
    avg_spend=('total_spend', 'mean')
).reset_index()

# Visualize how many items different customer groups buy
plt.figure(figsize=(10, 6))
ax = sns.barplot(data=basket_stats, x='lifestage', y='avg_items',
                 hue='customer_type', errorbar=None)
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
ax.spines['left'].set_visible(False)
ax.spines['bottom'].set_visible(False)
plt.grid(False)
plt.title('Average Items per Shopping Trip', fontsize=14, pad=20)
plt.ylabel('Number of Items', fontsize=12)
plt.xlabel('Customer Group', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.legend(title='Customer Type', frameon=False, bbox_to_anchor=(1.05, 1), loc='upper left')  # Fixed: changed 'upper_left' to 'upper left'

for p in ax.patches:
    ax.annotate(f"{p.get_height():.1f}",
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center',
                xytext=(0, 5),
                textcoords='offset points',
                fontsize=10)
plt.tight_layout()
plt.savefig('average_items_per_trip.png', bbox_inches='tight', dpi=300)
plt.show()

# Now look at spending patterns
plt.figure(figsize=(10, 6))
ax = sns.barplot(data=basket_stats, x='lifestage', y='avg_spend',
                 hue='customer_type', errorbar=None)
for spine in ax.spines.values():
    spine.set_visible(False)
plt.grid(False)
plt.title('Average Spend per Visit', fontsize=14, pad=20)
plt.ylabel('Amount Spent ($)', fontsize=12)
plt.xlabel('Customer Group', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.legend(title='Customer Type', frameon=False, bbox_to_anchor=(1.05, 1), loc='upper left')  # Fixed here too
ax.yaxis.set_major_formatter('${x:,.0f}')

for p in ax.patches:
    ax.annotate(f"${p.get_height():.0f}",
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center',
                xytext=(0, 5),
                textcoords='offset points',
                fontsize=10)
plt.tight_layout()
plt.savefig('average_spend_per_visit.png', bbox_inches='tight', dpi=300)
plt.show()

# Analyze shopping frequency patterns
visit_counts = merged_df.groupby('customer_id')['transaction_id'].nunique().reset_index()
visit_counts.columns = ['customer_id', 'visits']

visit_data = visit_counts.merge(
    merged_df[['customer_id', 'lifestage', 'customer_type']].drop_duplicates(),
    on='customer_id',
    how='left'
)

visit_stats = visit_data.groupby(['lifestage', 'customer_type']).agg(
    avg_visits=('visits', 'mean')
).reset_index()
```

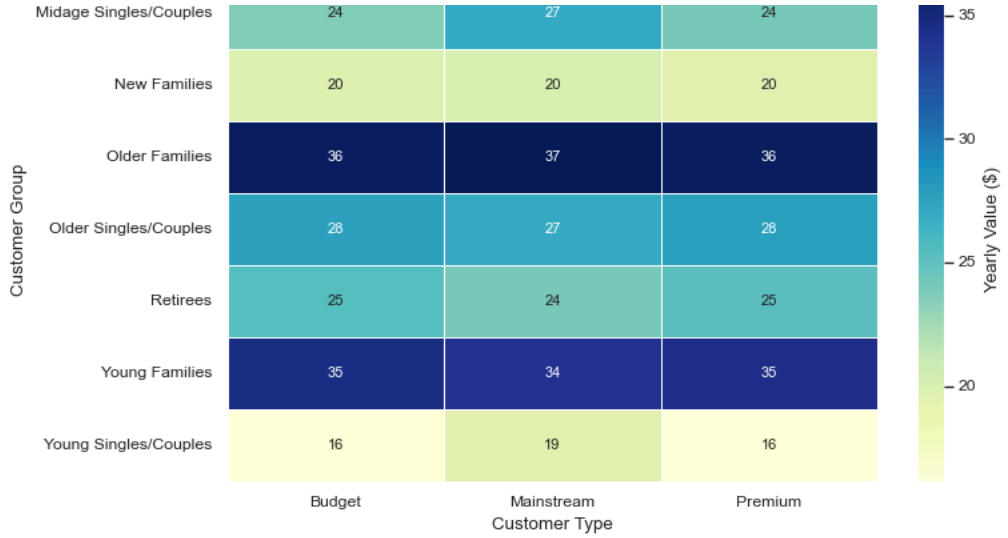
```
# Visualize visit frequency
plt.figure(figsize=(10, 6))
ax = sns.barplot(data=visit_stats, x='lifestage', y='avg_visits',
                 hue='customer_type', errorbar=None)
sns.despine(left=True, bottom=True, top=True, right=True)
plt.grid(False)
plt.title('How Often Customers Shop With Us', fontsize=14, pad=20)
plt.ylabel('Average Visits', fontsize=12)
plt.xlabel('Customer Group', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.legend(title='Customer Type', frameon=False, bbox_to_anchor=(1.05, 1), loc='upper left')  # And here

for p in ax.patches:
    ax.annotate(f"{p.get_height():.1f}",
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center',
                xytext=(0, 5),
                textcoords='offset points',
                fontsize=10)
plt.tight_layout()
plt.savefig('visit_frequency_by_segment.png', bbox_inches='tight', dpi=300)
plt.show()

# Combine metrics to understand customer value
customer_value = basket_stats.merge(visit_stats, on=['lifestage', 'customer_type'])
customer_value['yearly_value'] = customer_value['avg_spend'] * customer_value['avg_visits']

value_grid = customer_value.pivot(index='lifestage', columns='customer_type',
                                  values='yearly_value')

# Visualize customer value
plt.figure(figsize=(10, 6))
ax = sns.heatmap(value_grid, annot=True, fmt='.0f', cmap='YlGnBu',
                 linewidths=.5, cbar_kws={'label': 'Yearly Value ($)'},
                 annot_kws={'fontsize':10})
for spine in ax.spines.values():
    spine.set_visible(False)
plt.title('Estimated Yearly Customer Value', fontsize=14, pad=20)
plt.xlabel('Customer Type', fontsize=12)
plt.ylabel('Customer Group', fontsize=12)
plt.tight_layout()
plt.savefig('customer_value_heatmap.png', bbox_inches='tight', dpi=300)
plt.show()
```




Estimated Yearly Customer Value




**Summary of Findings:**

The analysis reveals that **Older Families and Young Families** exhibit the largest basket sizes (2.0 items) and highest transaction frequency (~~5 visits), indicating strong purchasing engagement, while **Young Singles/Couples (Budget & Premium)** show the smallest basket sizes (1.8 items) and lowest frequency~~ (2.4 visits), suggesting lower engagement. **Mainstream Midage Singles/Couples** spend the most per transaction $(7.69), whereas **Budget Young Singles/Couples **spend the least (6.64)$. Transaction frequency is highest among **Older Families (~5 visits)** and lowest among **Young Singles/Couples (~2.4 visits)**, with **New Families** also showing lower frequency (~2.7 visits). These insights highlight opportunities for segment-specific strategies—such as loyalty programs for frequent family shoppers and targeted promotions for young singles—to boost basket size, value, and retention.

....

.....

```
# Calculating total spend per customer
customer_spend = merged_df.groupby('customer_id')['total_sales'].sum().reset_index()
customer_spend.columns = ['customer_id', 'total_spent']

# Displaying the top 10 high-value customers
customer_spend.sort_values(by='total_spent', ascending=False).head(10)
```

| | customer_id | total_spent |
|---|---|---|
| **36308** | 226000 | 1300.00 |
| **37567** | 230078 | 138.60 |
| **61530** | 63197 | 132.80 |
| **46592** | 259009 | 127.20 |
| **17124** | 162039 | 126.80 |
| **60029** | 58361 | 124.80 |
| **37651** | 230154 | 124.40 |
| **71289** | 94185 | 122.80 |
| **8856** | 130090 | 122.65 |
| **22747** | 179228 | 120.80 |

```
sns.set_theme(style='whitegrid', palette='pastel')
```

```
# Average spend per transaction
avg_spend_per_txn = merged_df.groupby('customer_id')['total_sales'].mean().reset_index()
avg_spend_per_txn.columns = ['customer_id', 'avg_spend_per_txn']

# Displaying a sample
```

```
avg_spend_per_txn.head()
```

| | customer_id | avg_spend_per_txn |
|---|---|---|
| 0 | 1000 | 6.000000 |
| 1 | 10000 | 4.666667 |
| 2 | 100000 | 6.280000 |
| 3 | 100001 | 7.644444 |
| 4 | 100002 | 7.550000 |

```
# Transaction frequency per customer
txn_count_per_customer = merged_df.groupby('customer_id')['transaction_id'].nunique().reset_index()
txn_count_per_customer.columns = ['customer_id', 'num_transactions']

# top 10 customers by transaction count
txn_count_per_customer.head(10).sort_values(by='num_transactions', ascending=False)
```

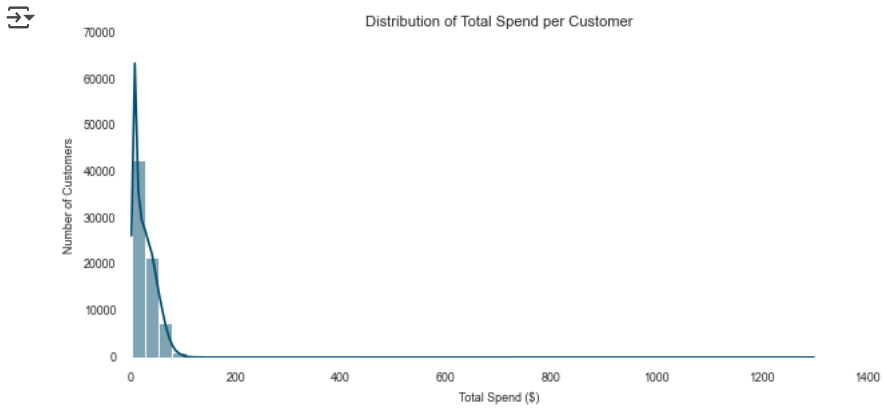
| | customer_id | num_transactions |
|---|---|---|
| 8 | 100006 | 13 |
| 3 | 100001 | 9 |
| 5 | 100003 | 9 |
| 4 | 100002 | 8 |
| 7 | 100005 | 7 |
| 6 | 100004 | 6 |
| 2 | 100000 | 5 |
| 9 | 100007 | 4 |
| 1 | 10000 | 3 |
| 0 | 1000 | 1 |

```
# Combining all metrics
customer_behavior = customer_spend.merge(avg_spend_per_txn, on='customer_id')
customer_behavior = customer_behavior.merge(txn_count_per_customer, on='customer_id')

# Previewing the merged metrics
customer_behavior.head(10).sort_values(by=['total_spent','avg_spend_per_txn'] , ascending=False)
```

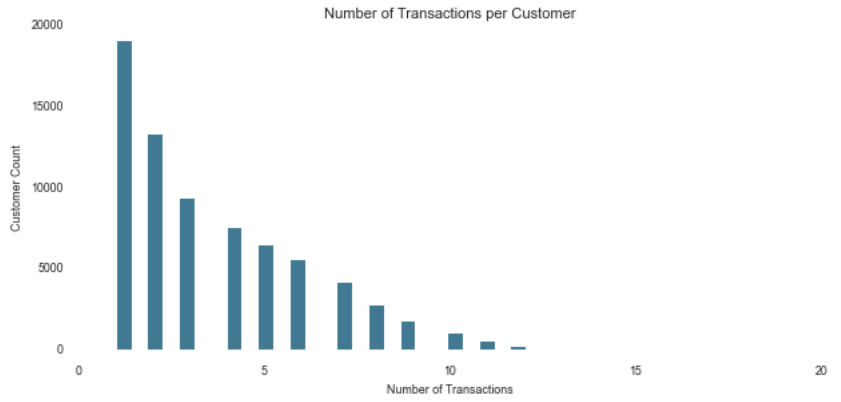
| | customer_id | total_spent | avg_spend_per_txn | num_transactions |
|---|---|---|---|---|
| 8 | 100006 | 89.6 | 6.892308 | 13 |
| 3 | 100001 | 68.8 | 7.644444 | 9 |
| 4 | 100002 | 60.4 | 7.550000 | 8 |
| 5 | 100003 | 53.6 | 5.955556 | 9 |
| 7 | 100005 | 47.5 | 6.785714 | 7 |
| 6 | 100004 | 41.8 | 6.966667 | 6 |
| 2 | 100000 | 31.4 | 6.280000 | 5 |
| 9 | 100007 | 21.2 | 5.300000 | 4 |
| 1 | 10000 | 14.0 | 4.666667 | 3 |
| 0 | 1000 | 6.0 | 6.000000 | 1 |

```
# Setting figure size
plt.figure(figsize=(8, 4))

# Creating the histogram with KDE
sns.histplot(customer_behavior['total_spent'], bins=50, kde=True, color="#004c6d")

# Setting the chart title and labels with appropriate font sizes
```

```
plt.title('Distribution of Total Spend per Customer', fontsize=10)
plt.xlabel('Total Spend ($)', fontsize=8)
plt.ylabel('Number of Customers', fontsize=8)

# Formatting ticks
plt.xticks(fontsize=8)
plt.yticks(fontsize=8)

# Removing spines for a cleaner look
sns.despine(top=True, right=True, left=True, bottom=True)

# Removing gridlines
plt.grid(False)

# Displaying the final professional chart
plt.tight_layout()
plt.savefig('customer_spend_distribution.png', bbox_inches='tight', dpi=300)
plt.show()
```




```
# Setting figure size
plt.figure(figsize=(8, 4))

# Creating the histogram without KDE
sns.histplot(customer_behavior['num_transactions'], bins=40, kde=False, color="#004c6d")

# Setting the chart title and axis labels
plt.title('Number of Transactions per Customer', fontsize=10)
plt.xlabel('Number of Transactions', fontsize=8)
plt.ylabel('Customer Count', fontsize=8)

# Formatting axis ticks
plt.xticks(fontsize=8)
plt.yticks(fontsize=8)

# Removing spines for a cleaner, modern presentation
sns.despine(top=True, right=True, left=True, bottom=True)

# Removing gridlines
plt.grid(False)

# Final layout adjustment and display
plt.tight_layout()
plt.savefig('customer_transaction_distribution.png', bbox_inches='tight', dpi=300)
plt.show()
```




```
# Setting up Seaborn visual style
sns.set_theme(style='whitegrid', palette='pastel')

# 2. Loading the dataset
# Assuming your DataFrame is already named `merged_df`
# merged_df = pd.read_csv('your_cleaned_data.csv')  # Uncomment and update if loading anew

# 3. Calculating customer purchase metrics
purchase_metrics = merged_df.groupby(['lifestage', 'customer_type']).agg(
    total_sales=('total_sales', 'sum'),
    total_quantity=('quantity', 'sum'),
    num_transactions=('transaction_id', 'nunique'),
    unique_customers=('customer_id', 'nunique')
).reset_index()

purchase_metrics['avg_sales_per_txn'] = purchase_metrics['total_sales'] / purchase_metrics['num_transactions']
purchase_metrics['avg_quantity_per_txn'] = purchase_metrics['total_quantity'] / purchase_metrics['num_transactions']

# 4. Formatting numeric columns with commas and dollar signs
purchase_metrics['total_sales'] = purchase_metrics['total_sales'].apply(lambda x: f"${x:,.2f}")
purchase_metrics['total_quantity'] = purchase_metrics['total_quantity'].apply(lambda x: f"{x:,.0f}")
purchase_metrics['num_transactions'] = purchase_metrics['num_transactions'].apply(lambda x: f"{x:,}")
purchase_metrics['unique_customers'] = purchase_metrics['unique_customers'].apply(lambda x: f"{x:,}")
purchase_metrics['avg_sales_per_txn'] = purchase_metrics['avg_sales_per_txn'].apply(lambda x: f"${x:,.2f}")
purchase_metrics['avg_quantity_per_txn'] = purchase_metrics['avg_quantity_per_txn'].apply(lambda x: f"{x:,.2f}")

# 5. Displaying the final formatted DataFrame
purchase_metrics.sort_values(by='total_sales', ascending=False, inplace=True)
purchase_metrics.reset_index(drop=True, inplace=True)
purchase_metrics
```

| | lifestage | customer_type | total_sales | total_quantity | num_transactions | unique_customers | avg_sales_per_txn | avg_quantity_per_t |
|---|---|---|---|---|---|---|---|---|
| 0 | Retirees | Premium | $97,646.05 | 24,884 | 13,036 | 3,872 | $7.49 | 1. |
| 1 | Young Families | Mainstream | $92,788.75 | 25,044 | 12,808 | 2,728 | $7.24 | 1. |
| 2 | Midage Singles/Couples | Mainstream | $90,803.85 | 22,699 | 11,801 | 3,340 | $7.69 | 1. |
| 3 | Young Families | Premium | $84,025.50 | 22,406 | 11,464 | 2,433 | $7.33 | 1. |
| 4 | Older Families | Premium | $81,958.40 | 22,171 | 11,078 | 2,274 | $7.40 | 2. |
| 5 | Young Singles/Couples | Budget | $61,141.60 | 16,671 | 9,214 | 3,779 | $6.64 | 1. |
| 6 | Midage Singles/Couples | Premium | $58,432.65 | 15,526 | 8,160 | 2,431 | $7.16 | 1. |
| 7 | Young Singles/Couples | Premium | $41,642.10 | 11,331 | 6,258 | 2,574 | $6.65 | 1. |
| 8 | Midage Singles/Couples | Budget | $35,514.80 | 9,496 | 4,988 | 1,504 | $7.12 | 1. |
| 9 | New Families | Budget | $21,928.45 | 5,571 | 2,991 | 1,112 | $7.33 | 1. |
| 10 | New Families | Mainstream | $17,013.90 | 4,319 | 2,321 | 849 | $7.33 | 1. |
| 11 | Older Families | Budget | $168,363.25 | 45,065 | 22,935 | 4,675 | $7.34 | 1. |
| 12 | Young Singles/Couples | Mainstream | $157,621.60 | 38,632 | 20,783 | 8,088 | $7.58 | 1. |
| 13 | Retirees | Mainstream | $155,677.05 | 40,518 | 21,363 | 6,479 | $7.29 | 1. |
| 14 | Young Families | Budget | $139,345.85 | 37,111 | 18,970 | 4,017 | $7.35 | 1. |
| 15 | Older Singles/Couples | Budget | $136,769.80 | 35,220 | 18,301 | 4,929 | $7.47 | 1. |
| 16 | Older | | | | | | | |

💡 Insights Top Spender: Customer 100006 leads in total spend at $89.60 across 13 transactions, indicating high engagement and loyalty.

Highest Avg Spend per Txn: Customer 100001 shows the highest average spend per transaction at $7.64, signaling premium purchase behavior.

Consistent Engagement: Several customers (e.g., 100001, 100002, 100003) maintain both high total spend and frequent transactions — ideal profiles for loyalty campaigns.

Low Activity Tiers: Customers like 1000 and 10000 demonstrate minimal interaction. These may benefit from targeted re-engagement strategies.

🧭 Strategic Implications Retention & Loyalty: Prioritize customers with high total spend and transaction count for exclusive offers or VIP programs.

Upsell Opportunities: Target customers with moderate engagement but strong average spend for bundle offers or larger packs.

Customer Lifecycle Management: Monitor customers with low frequency or spend to understand drop-off points and design timely nudges.

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## 📈 Time-Series Trend Analysis

### 🎯 Objective

- The aim is to evaluate sales performance over time to uncover purchasing cycles, seasonality, and momentum.
- This analysis will inform promotional timing, inventory planning, and long-term forecasting strategies.

```
# ✅ Code Block 1 – Convert Dates and Create Time Features

# Converting the transaction_date to datetime format
merged_df['transaction_date'] = pd.to_datetime(merged_df['transaction_date'])
```

```
# Creating a 'transaction_month' column for monthly trend aggregation
merged_df['transaction_month'] = merged_df['transaction_date'].dt.to_period('M').astype(str)

# Preview the result to confirm
merged_df[['transaction_date', 'transaction_month']].head()
```

| | transaction_date | transaction_month |
|---|---|---|
| 0 | 2018-10-17 | 2018-10 |
| 1 | 2019-05-14 | 2019-05 |
| 2 | 2019-05-20 | 2019-05 |
| 3 | 2018-08-17 | 2018-08 |
| 4 | 2018-08-18 | 2018-08 |

```
# Aggregating total sales and quantity by month
monthly_trends = merged_df.groupby('transaction_month').agg({
    'total_sales': 'sum',
    'quantity': 'sum',
    'transaction_id': pd.Series.nunique
}).reset_index()

# Renaming columns for clarity
monthly_trends.columns = ['Month', 'Total Sales', 'Total Quantity Sold', 'Number of Transactions']

# Formatting numbers
monthly_trends['Total Sales'] = monthly_trends['Total Sales'].apply(lambda x: f"${x:,.2f}")
monthly_trends['Total Quantity Sold'] = monthly_trends['Total Quantity Sold'].apply(lambda x: f"{x:,}")
monthly_trends['Number of Transactions'] = monthly_trends['Number of Transactions'].apply(lambda x: f"{x:,}")

monthly_trends.head(10)
```

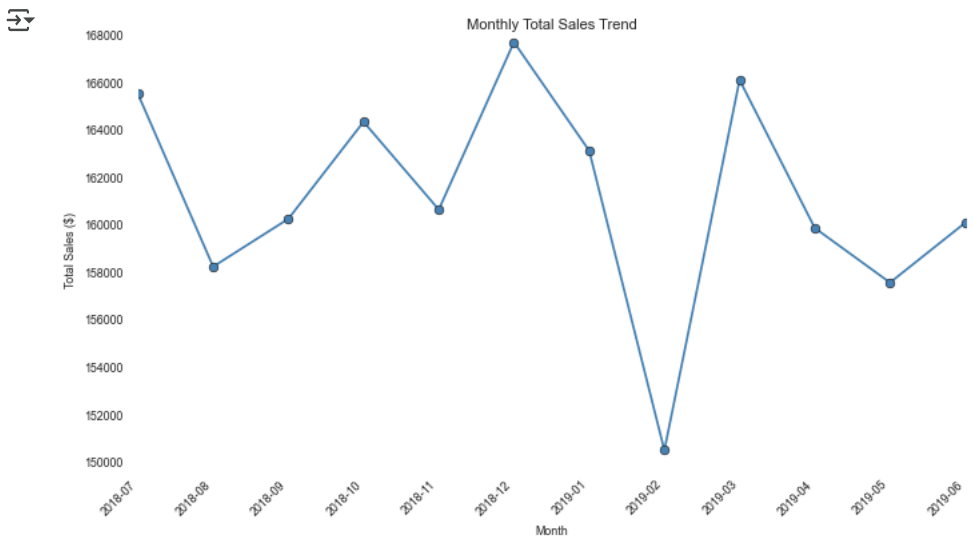
| | Month | Total Sales | Total Quantity Sold | Number of Transactions |
|---|---|---|---|---|
| 0 | 2018-07 | $165,555.80 | 43,275 | 22,480 |
| 1 | 2018-08 | $158,275.85 | 41,520 | 22,308 |
| 2 | 2018-09 | $160,291.20 | 41,803 | 21,656 |
| 3 | 2018-10 | $164,382.20 | 42,846 | 22,208 |
| 4 | 2018-11 | $160,681.60 | 41,936 | 21,758 |
| 5 | 2018-12 | $167,741.00 | 43,782 | 22,742 |
| 6 | 2019-01 | $163,164.80 | 42,555 | 22,062 |
| 7 | 2019-02 | $150,535.30 | 39,243 | 20,325 |
| 8 | 2019-03 | $166,146.30 | 43,333 | 22,500 |
| 9 | 2019-04 | $159,905.50 | 41,771 | 21,690 |

```
# Re-aggregating with unformatted values for plotting
plot_data = merged_df.groupby('transaction_month').agg({
    'total_sales': 'sum',
    'quantity': 'sum'
}).reset_index()

# Plotting
plt.figure(figsize=(10, 5))
plt.plot(plot_data['transaction_month'], plot_data['total_sales'], color='steelblue', marker='o')
plt.title('Monthly Total Sales Trend', fontsize=10)
plt.xlabel('Month', fontsize=8)
plt.ylabel('Total Sales ($)', fontsize=8)

# Formatting aesthetics
plt.xticks(rotation=45, ha='right', fontsize=8)
plt.yticks(fontsize=8)
plt.grid(False)
for spine in plt.gca().spines.values():
    spine.set_visible(False)
```

```
plt.savefig('monthly_sales_trend.png', bbox_inches='tight', dpi=300)
plt.show()
```



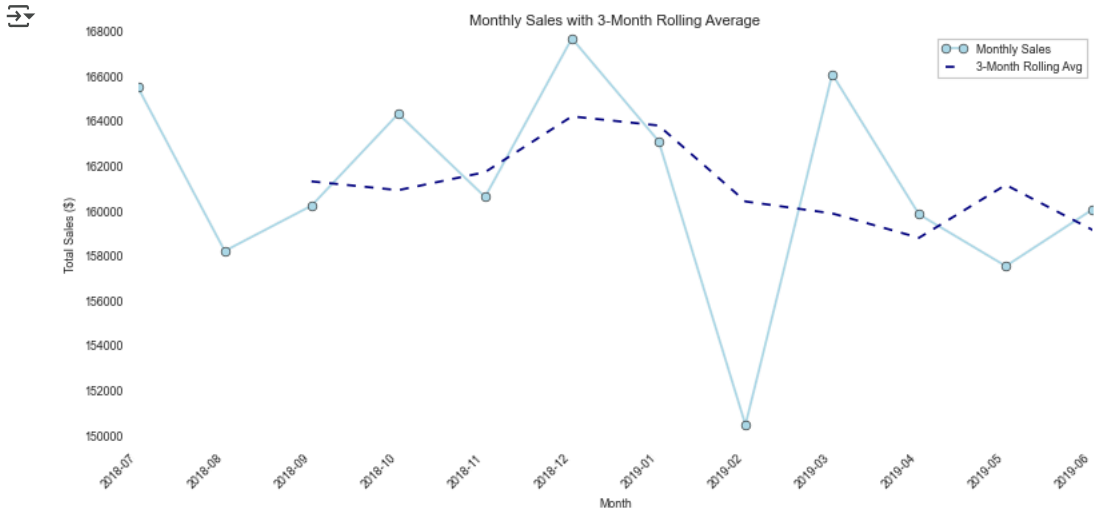

```
# Adding rolling average for smoother trend visualization
plot_data['Rolling Avg (3 Months)'] = plot_data['total_sales'].rolling(window=3).mean()

# Plotting
plt.figure(figsize=(10, 5))
plt.plot(plot_data['transaction_month'], plot_data['total_sales'], label='Monthly Sales', color='lightblue', marker='o')
plt.plot(plot_data['transaction_month'], plot_data['Rolling Avg (3 Months)'], label='3-Month Rolling Avg', color='navy', linestyle='--')

plt.title('Monthly Sales with 3-Month Rolling Average', fontsize=10)
plt.xlabel('Month', fontsize=8)
plt.ylabel('Total Sales ($)', fontsize=8)

plt.xticks(rotation=45, ha='right', fontsize=8)
plt.yticks(fontsize=8)
plt.grid(False)
for spine in plt.gca().spines.values():
    spine.set_visible(False)

plt.legend(fontsize=8)
plt.tight_layout()
plt.savefig('monthly_sales_trend_with_rolling_avg.png', bbox_inches='tight', dpi=300)
plt.show()
```




```
# Extracting the day of the week
merged_df['transaction_day'] = merged_df['transaction_date'].dt.day_name()

# Aggregating total sales per day
```

```
sales_by_day = (
    merged_df.groupby('transaction_day')['total_sales']
    .sum()
    .reindex(['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday'])
    .reset_index()
)

# Formatting total_sales with dollar sign and commas
sales_by_day['total_sales'] = sales_by_day['total_sales'].apply(lambda x: f"${x:,.2f}")

# Displaying results
sales_by_day.sort_values(by='total_sales', ascending=False, inplace=True)
sales_by_day
```

| | transaction_day | total_sales |
|---|---|---|
| **6** | Sunday | $283,276.45 |
| **4** | Friday | $279,365.70 |
| **2** | Wednesday | $277,849.25 |
| **5** | Saturday | $275,650.50 |
| **0** | Monday | $274,923.45 |
| **3** | Thursday | $272,981.80 |
| **1** | Tuesday | $270,361.85 |

```
# Re-aggregating without formatting for plotting
raw_sales_by_day = (
    merged_df.groupby('transaction_day')['total_sales']
    .sum()
    .reindex(['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday'])
    .reset_index()
)

# Chart
import matplotlib.pyplot as plt
import seaborn as sns

# Plot style for a professional aesthetic
plt.style.use('ggplot')
sns.set_palette('pastel')

plt.figure(figsize=(10, 5))
ax = sns.barplot(data=raw_sales_by_day, x='transaction_day', y='total_sales')
plt.title('Total Sales by Day of the Week', fontsize=10)
plt.xlabel('Day of Week', fontsize=8)
plt.ylabel('Total Sales ($)', fontsize=8)

# Add numbers on top of each bar
for p in ax.patches:
    ax.annotate(f"${p.get_height():,.0f}",
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center',
                xytext=(0, 5),
                textcoords='offset points',
                fontsize=8)

# Remove gridlines and spines
plt.grid(False)
sns.despine()

# Format y-axis with dollar formatting
from matplotlib.ticker import FuncFormatter
plt.gca().yaxis.set_major_formatter(FuncFormatter(lambda x, _: f'${x:,.0f}'))

plt.tight_layout()
```