In [ ]:

Quantium Data Analytics Virtual Experience Program

Task 1: Data Preparation and Customer Analytics

Background

You are a member of Quantium's retail analytics team, and your client, Julia, the Category Manager for Chips, needs your expertise to better understand customer purchasing behaviors and inform the supermarket's strategic plan for the chip category.

Objective

Analyze the transaction dataset to identify customer segments and their chip purchasing behaviors, providing data-driven insights and commercial recommendations for Julia's category review.

Task

Data Checks

- Create and interpret summaries of the data
- Identify and remove outliers (if applicable)
- Check and correct data formats (if applicable)

Derive Extra Features

- Pack size
- Brand name

Define Metrics of Interest

- Who spends on chips
- What drives spending for each customer segment

Key Customer Attributes

- **LIFESTAGE**: Identifies customers' life stages (e.g., family size, children's ages)
- **PREMIUM_CUSTOMER**: Segments customers by price point and product type preferences (quality/brand vs. cheapest options)

Deliverable

Provide a strategic recommendation to Julia, supported by data insights, to inform the chip category strategy for the next half year. Ensure your insights have commercial applications.

In [10]:
```
#   Importing the necessary libraries/modules.

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import datetime
# import xlrd
%matplotlib inline

#   Ignoring any warnings.

import warnings
warnings.simplefilter(action="ignore", category=FutureWarning)
```

In [11]:
```
transaction_data=pd.read_csv("QVI_transaction_data.csv") #   Reading the Excel Work
transaction_data
```

Out[11]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD
0	43390	1	1000	1	5	Natural Chip Compny SeaSalt175g	
1	43599	1	1307	348	66	CCs Nacho Cheese 175g	
2	43605	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	
3	43329	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	
4	43330	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	
...	...	...	...	...	...	...	
264831	43533	272	272319	270088	89	Kettle Sweet Chilli And Sour Cream 175g	
264832	43325	272	272358	270154	74	Tostitos Splash Of Lime 175g	
264833	43410	272	272379	270187	51	Doritos Mexicana 170g	
264834	43461	272	272379	270188	42	Doritos Corn Chip Mexican Jalapeno 150g	
264835	43365	272	272380	270189	74	Tostitos Splash Of Lime 175g	

264836 rows × 8 columns

In [12]:

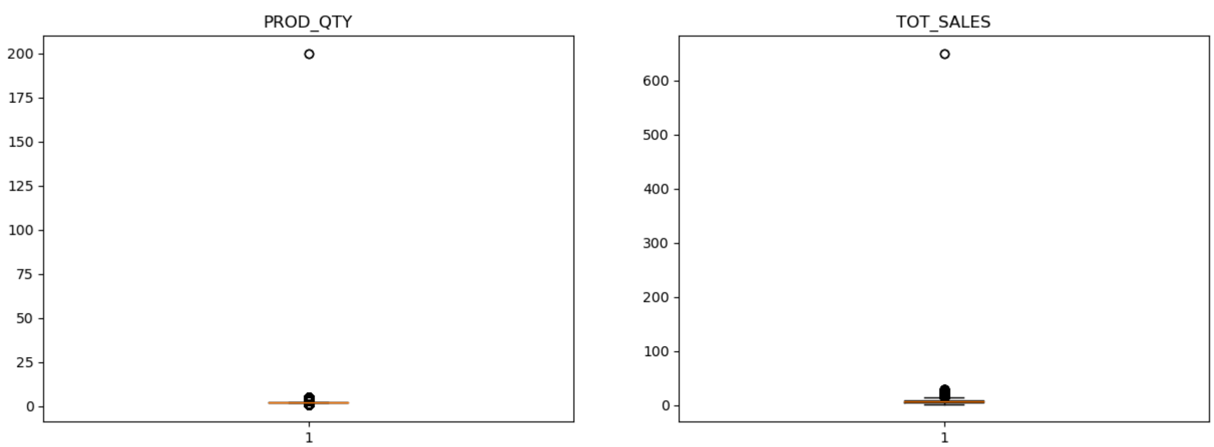
```
transaction_data.info() #   Getting a concise summary of the pandas.DataFrame.
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264836 entries, 0 to 264835
Data columns (total 8 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   DATE            264836 non-null  int64  
 1   STORE_NBR       264836 non-null  int64  
 2   LYLTY_CARD_NBR  264836 non-null  int64  
 3   TXN_ID          264836 non-null  int64  
 4   PROD_NBR        264836 non-null  int64  
 5   PROD_NAME       264836 non-null  object 
 6   PROD_QTY        264836 non-null  int64  
 7   TOT_SALES       264836 non-null  float64
dtypes: float64(1), int64(6), object(1)
memory usage: 16.2+ MB
```

In [13]:
```python
transaction_data.isnull().sum() #   Checking for any null values in the pandas.Data
```

Out[13]:
```
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
```

In [14]:
```python
#   Checking for any outliers in the pandas.DataFrame using a box plot of the PROD_

figure, axis=plt.subplots(1, 2, figsize=(15, 5))
axis[0].boxplot(transaction_data["PROD_QTY"])
axis[1].boxplot(transaction_data["TOT_SALES"])
axis[0].set_title("PROD_QTY")
axis[1].set_title("TOT_SALES")
plt.show()
```



In [15]:
```python
#   Removing the outliers from the pandas.DataFrame.

transaction_data=transaction_data[transaction_data["PROD_QTY"]<100]
transaction_data=transaction_data[transaction_data["TOT_SALES"]<500]
```

```
transaction_data=transaction_data.reset_index(drop=True)    #   Resetting the index
transaction_data
```

Out[15]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD
0	43390	1	1000	1	5	Natural Chip Compny SeaSalt175g	
1	43599	1	1307	348	66	CCs Nacho Cheese 175g	
2	43605	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	
3	43329	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	
4	43330	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	
...	...	...	...	...	...	...	
264829	43533	272	272319	270088	89	Kettle Sweet Chilli And Sour Cream 175g	
264830	43325	272	272358	270154	74	Tostitos Splash Of Lime 175g	
264831	43410	272	272379	270187	51	Doritos Mexicana 170g	
264832	43461	272	272379	270188	42	Doritos Corn Chip Mexican Jalapeno 150g	
264833	43365	272	272380	270189	74	Tostitos Splash Of Lime 175g	

264834 rows × 8 columns

As we can see, removing the outliers decreased the pandas.DataFrame down two rows. Of course, this isn't a significant difference, but removing these outliers may allow us to get slightly more accurate analysis results.

Unfortunately, we can also see that the DATE column in the dataset is in the Microsoft Excel serial time format, which is the number of days since the number of days since 1st Janurary 1900, so it's better to convert it to the appropriate datetime format that's more familiar to us.

In [16]:
```
transaction_data["DATE"] = pd.to_datetime(transaction_data["DATE"], unit="D", origi
```

In [17]:
```
transaction_data
```

Out[17]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD
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	
...	...	...	...	...	...	...	
264829	2019-03-09	272	272319	270088	89	Kettle Sweet Chilli And Sour Cream 175g	
264830	2018-08-13	272	272358	270154	74	Tostitos Splash Of Lime 175g	
264831	2018-11-06	272	272379	270187	51	Doritos Mexicana 170g	
264832	2018-12-27	272	272379	270188	42	Doritos Corn Chip Mexican Jalapeno 150g	
264833	2018-09-22	272	272380	270189	74	Tostitos Splash Of Lime 175g	

264834 rows × 8 columns

In [18]:
```
purchase_behaviour=pd.read_csv("QVI_purchase_behaviour.csv")    #   Reading the CSV
purchase_behaviour
```

Out[18]:

	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
...	...	...	...
72632	2370651	MIDAGE SINGLES/COUPLES	Mainstream
72633	2370701	YOUNG FAMILIES	Mainstream
72634	2370751	YOUNG FAMILIES	Premium
72635	2370961	OLDER FAMILIES	Budget
72636	2373711	YOUNG SINGLES/COUPLES	Mainstream

72637 rows × 3 columns

In [19]:

```
purchase_behaviour.info()  #   Getting a concise summary of the pandas.DataFrame.
```

```
<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 [20]:

```
purchase_behaviour.isnull().sum()    #   Checking for any null values in the pandas.
```

Out[20]:

```
LYLTY_CARD_NBR      0
LIFESTAGE           0
PREMIUM_CUSTOMER    0
dtype: int64
```

In [21]:

```
dataframe=pd.merge(transaction_data, purchase_behaviour, on="LYLTY_CARD_NBR")    #
dataframe
```

Out[21]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD
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	
...	...	...	...	...	...	...	
264829	2019-03-09	272	272319	270088	89	Kettle Sweet Chilli And Sour Cream 175g	
264830	2018-08-13	272	272358	270154	74	Tostitos Splash Of Lime 175g	
264831	2018-11-06	272	272379	270187	51	Doritos Mexicana 170g	
264832	2018-12-27	272	272379	270188	42	Doritos Corn Chip Mexican Jalapeno 150g	
264833	2018-09-22	272	272380	270189	74	Tostitos Splash Of Lime 175g	

264834 rows × 10 columns

In [22]:

```
unique_products=list(dataframe["PROD_NAME"].unique())   #   Storing the distinct pr
print("Total Distinct Products:", len(unique_products))
```

```
Total Distinct Products: 114
```

In [23]:

```
dataframe["PROD_NAME_CLEAN"]=dataframe["PROD_NAME"].str.replace("\d+g", "") #   Rem
dataframe["PROD_SIZE"]=dataframe["PROD_NAME"].str.extract("(\d+)")     #   Extractin
dataframe["PROD_NAME"]=dataframe["PROD_NAME_CLEAN"] #   Assigning the PROD_NAME_CLE
dataframe=dataframe.drop("PROD_NAME_CLEAN", axis=1) #   Dropping the PROD_NAME_CLEA
dataframe["BRAND_NAME"]=dataframe["PROD_NAME"].str.split().str[0]     #   Extracting
dataframe=dataframe.loc[:, ["DATE", "STORE_NBR", "LYLTY_CARD_NBR", "TXN_ID", "PROD_
dataframe
```

Out[23]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD
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	
...	...	...	...	...	...	...	
264829	2019-03-09	272	272319	270088	89	Kettle Sweet Chilli And Sour Cream 175g	
264830	2018-08-13	272	272358	270154	74	Tostitos Splash Of Lime 175g	
264831	2018-11-06	272	272379	270187	51	Doritos Mexicana 170g	
264832	2018-12-27	272	272379	270188	42	Doritos Corn Chip Mexican Jalapeno 150g	
264833	2018-09-22	272	272380	270189	74	Tostitos Splash Of Lime 175g	

264834 rows × 12 columns

In [24]:

```
dataframe.isnull().sum()   #   Checking for any null values in the pandas.DataFrame
```

Out[24]:
```
DATE                0
STORE_NBR           0
LYLTY_CARD_NBR      0
TXN_ID              0
PROD_NBR            0
PROD_NAME           0
PROD_SIZE           0
BRAND_NAME          0
PROD_QTY            0
TOT_SALES           0
LIFESTAGE           0
PREMIUM_CUSTOMER    0
dtype: int64
```

In [25]:
```
dataframe=dataframe.sort_values(by="DATE")  #   Sorting the pandas.DataFrame in asc
dataframe=dataframe.reset_index(drop=True)  #   Resetting the index of the pandas.D
dataframe
```

Out[25]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD
0	2018-07-01	24	24109	20881	54	CCs Original 175g	
1	2018-07-01	236	236023	238660	100	Smiths Crinkle Cut Chips Chs&Onion170g	
2	2018-07-01	45	45100	40977	47	Doritos Corn Chips Original 170g	
3	2018-07-01	21	21284	17968	59	Old El Paso Salsa Dip Tomato Med 300g	
4	2018-07-01	262	262188	262373	114	Kettle Sensations Siracha Lime 150g	
...	...	...	...	...	...	...	
264829	2019-06-30	26	26054	22482	34	Pringles Slt Vingar 134g	
264830	2019-06-30	201	201371	201571	36	Kettle Chilli 175g	
264831	2019-06-30	222	222089	222019	114	Kettle Sensations Siracha Lime 150g	
264832	2019-06-30	230	230102	232603	52	Grain Waves Sour Cream&Chives 210G	
264833	2019-06-30	28	28004	24553	98	NCC Sour Cream & Garden Chives 175g	

264834 rows × 12 columns

Now that we have the pandas.DataFrame sorted according to the date, we can analyse the dataset with regards to the change over time. However, before we can do that, we need to make sure that the DATE column contains no missing values for unrecorded dates.

In [26]:

```
pd.date_range(start="2018-07-01", end="2019-06-30").difference(dataframe["DATE"])
```

Out[26]:

```
DatetimeIndex(['2018-12-25'], dtype='datetime64[ns]', freq='D')
```

As suspected, there is one unrecorded date and that's for Christmas Day, since most stores are closed during that time. Hence, we can fill in the value for this as having zero sales on the date.

In [28]:
```
#   Adding an entry for the missing date in the pandas.DataFrame.

dataframe.loc[len(dataframe)] = [pd.to_datetime("2018-12-25"), 0, 0, 0, 0, "None",
dataframe = dataframe.sort_values(by="DATE")
dataframe = dataframe.reset_index(drop=True)
```

In [29]:
```
dataframe.loc[dataframe["DATE"]=="2018-12-25"]  #   Checking if the missing date ha
```

Out[29]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_S
129324	2018-12-25	0	0	0	0	None	N(

With our missing date sorted, let's start by visualising the change in total sales over the entire recorded duration.

In [30]:
```
date_sales=dataframe.groupby("DATE")["TOT_SALES"].sum().reset_index()   #   Groupin
date_sales
```

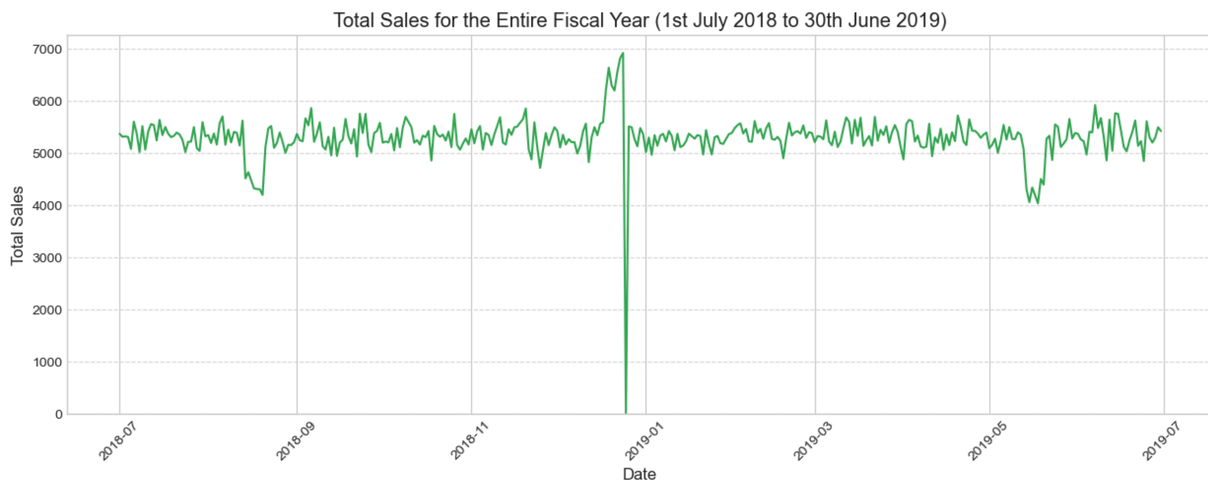
Out[30]:

	DATE	TOT_SALES
0	2018-07-01	5372.2
1	2018-07-02	5315.4
2	2018-07-03	5321.8
3	2018-07-04	5309.9
4	2018-07-05	5080.9
...	...	...
360	2019-06-26	5305.0
361	2019-06-27	5202.8
362	2019-06-28	5299.6
363	2019-06-29	5497.6
364	2019-06-30	5423.4

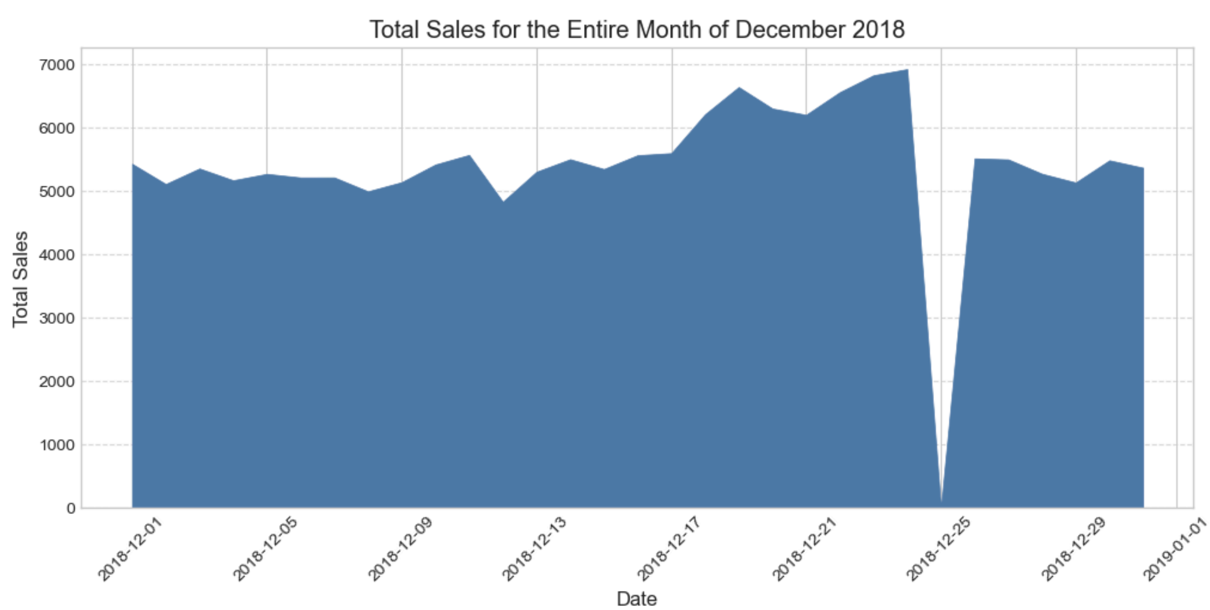
365 rows × 2 columns

In [71]:
```
#   Plotting a line graph of the total sales for each date over the entire recorded

import seaborn as sns

plt.figure(figsize=(15, 5))
```

```
sns.lineplot(x="DATE", y="TOT_SALES", data=date_sales, color="#34A853")
plt.title("Total Sales for the Entire Fiscal Year (1st July 2018 to 30th June 2019)
plt.xlabel("Date")
plt.ylabel("Total Sales")
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.xticks(rotation=45)
plt.ylim(bottom=0)
sns.set_style("whitegrid")  # Use seaborn's API to set the style
plt.show()
```



In [74]:
```
#   Plotting a line graph of the total sales for each recorded date during December

plt.figure(figsize=(12, 5))
plt.fill_between(date_sales["DATE"][date_sales["DATE"].dt.month==12], date_sales["T
plt.title("Total Sales for the Entire Month of December 2018")
plt.xlabel("Date")
plt.ylabel("Total Sales")
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.xticks(rotation=45)
plt.ylim(bottom=0)
plt.show()
```



As suspected, the sales reached an all-time high the day before Christmas Day, which makes sense because people tend to purchase food items more when approaching holiday season. We can also see a consistent rise in the line graph between 21st December and 24th December, which means that these are the dates the store could target with promotions and discounts to increase the sales even more.

If the store does want to target these dates, it would be important to know which package sizes sell the most to create promotions and discounts around them.

In [33]:
```
holiday_sales=dataframe[(dataframe["DATE"]>="2018-12-21") & (dataframe["DATE"]<="20
holiday_sales=holiday_sales.sort_values(by="TOT_SALES") #   Sorting the pandas.Data
holiday_sales=holiday_sales.reset_index(drop=True)  #   Resetting the index of the
holiday_sales
```

Out[33]:

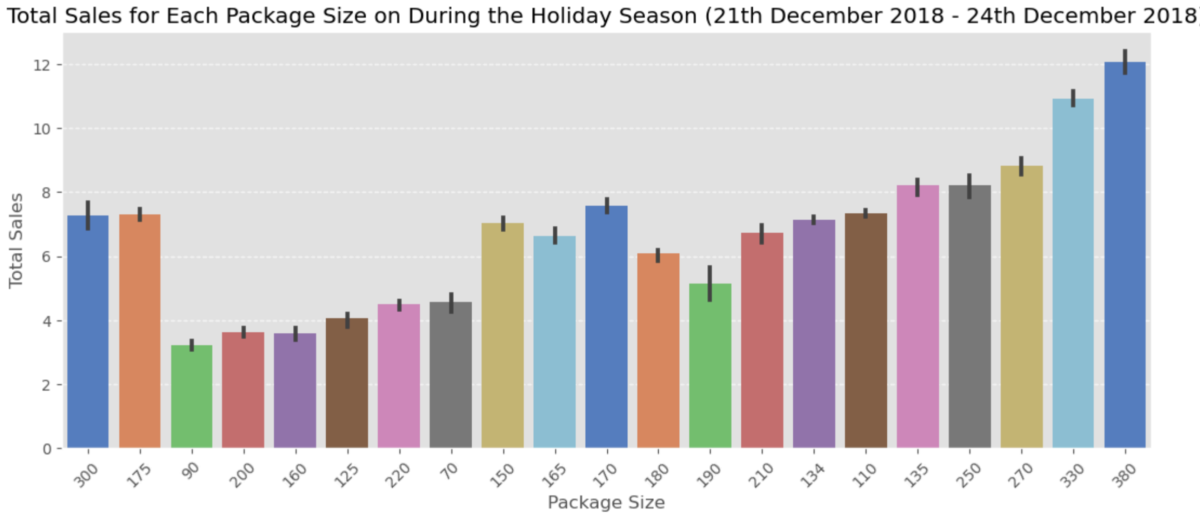
	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_SIZI
0	2018-12-22	127	127448	130458	76	Woolworths Medium Salsa 300g	30(
1	2018-12-24	38	38005	34012	35	Woolworths Mild Salsa 300g	30(
2	2018-12-23	255	255077	254619	76	Woolworths Medium Salsa 300g	30(
3	2018-12-22	186	186218	188613	76	Woolworths Medium Salsa 300g	30(
4	2018-12-22	136	136114	138499	35	Woolworths Mild Salsa 300g	30(
...	...	...	...	...	...	...	..
3608	2018-12-24	217	217332	217772	4	Dorito Corn Chp Supreme 380g	38(
3609	2018-12-22	237	237075	240397	4	Dorito Corn Chp Supreme 380g	38(
3610	2018-12-24	231	231128	234222	4	Dorito Corn Chp Supreme 380g	38(
3611	2018-12-22	54	54377	48429	4	Dorito Corn Chp Supreme 380g	38(
3612	2018-12-24	21	21168	17783	4	Dorito Corn Chp Supreme 380g	38(

3613 rows × 12 columns

In [69]:

```
#   Plotting a bar graph of the total sales for each package size between 21st Dece

plt.figure(figsize=(13, 5))
sns.barplot(x="PROD_SIZE", y="TOT_SALES", data=holiday_sales, palette="muted")
plt.title("Total Sales for Each Package Size on During the Holiday Season (21th Dec
plt.xlabel("Package Size")
plt.ylabel("Total Sales")
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.xticks(rotation=45)
plt.ylim(bottom=0)
```

```
plt.style.use('ggplot')
plt.show()
```



It seems like customers mostly purchased the 380 gramme package size (the largest one in the store) when approaching the holiday season.

Additionally, we can also find the brands that sold the most during the particular dates for brand-specific campaigns.

In [36]:
```
holiday_brands=holiday_sales.groupby("BRAND_NAME")["TOT_SALES"].sum().reset_index()
holiday_brands=holiday_brands.reset_index(drop=True)    #   Resetting the index of
holiday_brands
```

Out[36]:

	BRAND_NAME	TOT_SALES
0	Kettle	4940.0
1	Doritos	2948.5
2	Smiths	2914.5
3	Pringles	2290.3
4	Thins	1343.1

We can see that KETTLE® was the highest-selling brand during the holiday season, so it'd be wise to surround promotions and discounts around it to drive sales even more.

Let's see if our holiday season statistics match with the ones during the entire duration of the recorded sales.

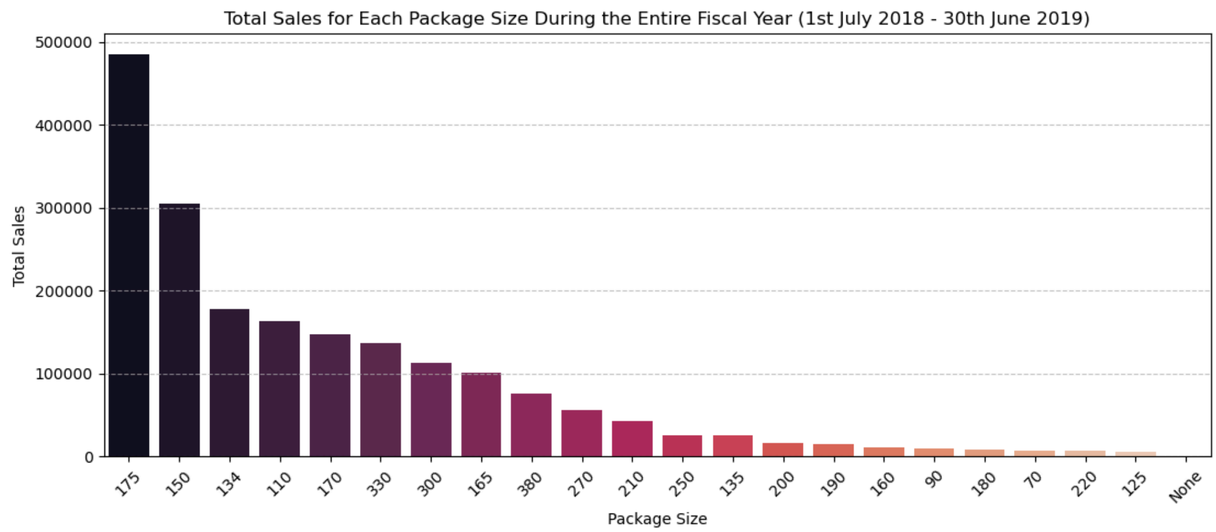
In [37]:
```
package_sales=dataframe.groupby("PROD_SIZE")["TOT_SALES"].sum().reset_index().sort_
package_sales=package_sales.reset_index(drop=True)    #   Resetting the index of th
package_sales
```

Out[37]:

	PROD_SIZE	TOT_SALES
0	175	485437.4
1	150	304288.5
2	134	177655.5
3	110	162765.4
4	170	146673.0
5	330	136794.3
6	300	113330.6
7	165	101360.6
8	380	75419.6
9	270	55425.4
10	210	43048.8
11	250	26096.7
12	135	26090.4
13	200	16007.5
14	190	14412.9
15	160	10647.6
16	90	9676.4
17	180	8568.4
18	70	6852.0
19	220	6831.0
20	125	5733.0
21	None	0.0

In [64]:

```
#   Plotting a bar graph of the total sales for each package size during the entire

plt.figure(figsize=(13, 5))
sns.barplot(x="PROD_SIZE", y="TOT_SALES", data=package_sales, palette="rocket")
plt.title("Total Sales for Each Package Size During the Entire Fiscal Year (1st Jul
plt.xlabel("Package Size")
plt.ylabel("Total Sales")
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.xticks(rotation=45)
plt.ylim(bottom=0)
plt.show()
```



As we can see, the 175 gramme package size was the highest-selling one over the entire duration of the recorded sales, and even that by nearly 37% from the second highest-selling package size. Hence, it's clear that the 175 gramme package size is a customer favourite!

Likewise, we can also check for the highest-selling brands during the entire duration of the recorded sales.

In [39]:
```
brands_sales=dataframe.groupby("BRAND_NAME")["TOT_SALES"].sum().reset_index().sort_
brands_sales=brands_sales.reset_index(drop=True)    #   Resetting the index of the
brands_sales
```

Out[39]:

	BRAND_NAME	TOT_SALES
0	Kettle	390239.8
1	Smiths	210076.8
2	Doritos	201538.9
3	Pringles	177655.5
4	Old	90785.1

Just like the holiday season sales, KETTLE® remained the highest-selling brand during the entire duration of the recorded sales.

With the brand and product analysis done, we can move onto the customer analysis now. The first part would be analyse which sort of customers are the most loyal to the store, which would also be the ones that have the most purchases from it.

In [40]:
```
dataframe["LIFESTAGE"].value_counts()   #   Finding the number of entries for each
```

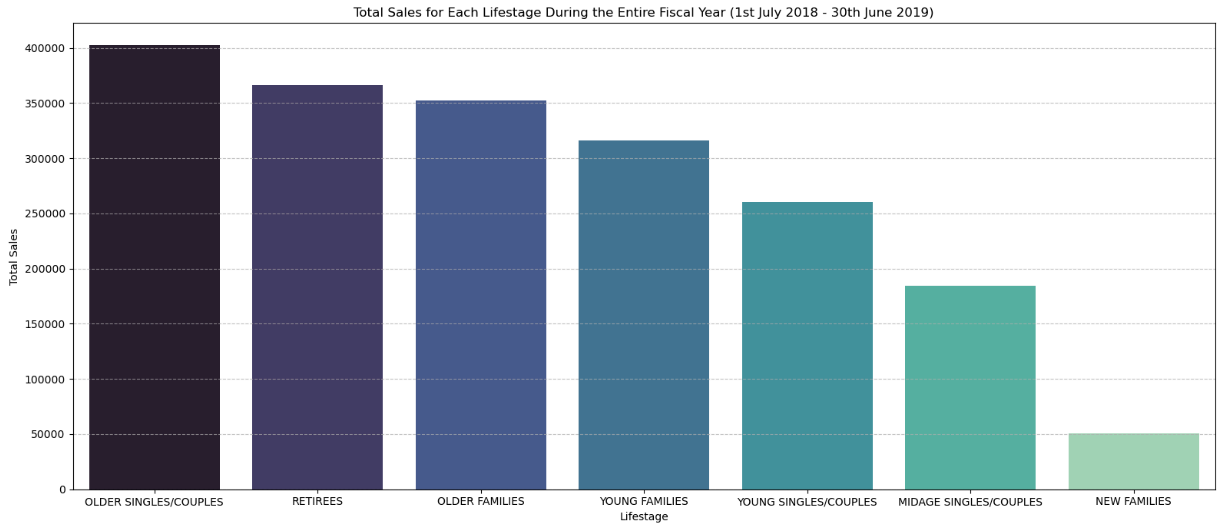
Out[40]:
```
LIFESTAGE
OLDER SINGLES/COUPLES     54479
RETIREES                  49763
OLDER FAMILIES            48594
YOUNG FAMILIES            43592
YOUNG SINGLES/COUPLES     36377
MIDAGE SINGLES/COUPLES    25110
NEW FAMILIES               6919
None                          1
Name: count, dtype: int64
```

In [41]:
```
customer_sales=dataframe.groupby("LIFESTAGE")["TOT_SALES"].sum().reset_index().sort
customer_sales=customer_sales.reset_index(drop=True)    #   Resetting the index of
customer_sales
```

Out[41]:

	LIFESTAGE	TOT_SALES
0	OLDER SINGLES/COUPLES	402426.75
1	RETIREES	366470.90
2	OLDER FAMILIES	352467.20
3	YOUNG FAMILIES	316160.10
4	YOUNG SINGLES/COUPLES	260405.30
5	MIDAGE SINGLES/COUPLES	184751.30
6	NEW FAMILIES	50433.45

In [61]:
```
#   Plotting a bar graph of the total sales for each lifestage during the entire re

plt.figure(figsize=(16, 7))
sns.barplot(x="LIFESTAGE", y="TOT_SALES", data=customer_sales, palette="mako")
plt.title("Total Sales for Each Lifestage During the Entire Fiscal Year (1st July 2
plt.xlabel("Lifestage")
plt.ylabel("Total Sales")
plt.tight_layout()
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



It seems like OLDER SINGLES/COUPLES are the most loyal customers of the store and NEW FAMILIES are the least. Interestingly, we can see a decreasing trend of purchases according to age in the first half of the bar graph, with customers that are the most likely to spend the most time at home also having the most purchases, even though snack items wouldn't logically be associated with an age demographic.

In [43]:
```
lifestage_sales=dataframe.groupby(["LIFESTAGE", "DATE"])["TOT_SALES"].sum().reset_i
lifestage_sales=lifestage_sales[lifestage_sales["LIFESTAGE"]!="None"]   #   Removin
lifestage_sales
```

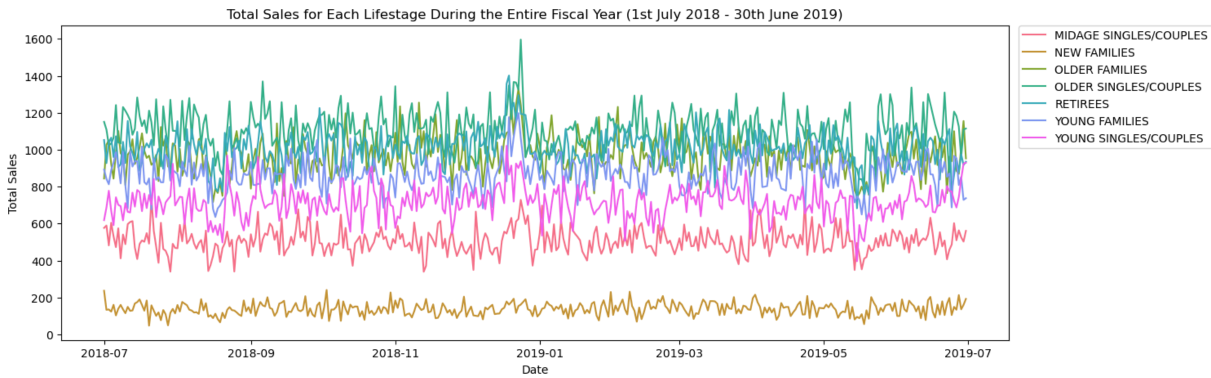
Out[43]:

	LIFESTAGE	DATE	TOT_SALES
0	MIDAGE SINGLES/COUPLES	2018-07-01	576.8
1	MIDAGE SINGLES/COUPLES	2018-07-02	589.5
2	MIDAGE SINGLES/COUPLES	2018-07-03	482.2
3	MIDAGE SINGLES/COUPLES	2018-07-04	604.5
4	MIDAGE SINGLES/COUPLES	2018-07-05	531.6
...	...	...	...
2544	YOUNG SINGLES/COUPLES	2019-06-26	687.4
2545	YOUNG SINGLES/COUPLES	2019-06-27	743.4
2546	YOUNG SINGLES/COUPLES	2019-06-28	840.7
2547	YOUNG SINGLES/COUPLES	2019-06-29	924.5
2548	YOUNG SINGLES/COUPLES	2019-06-30	929.9

2548 rows × 3 columns

In [58]:
```
#   Plotting a multi-line graph of the total sales for each lifestage during the en

plt.figure(figsize=(15, 5))
```

```
sns.set_palette(sns.dark_palette("#FFC107", n_colors=4))
sns.lineplot(x="DATE", y="TOT_SALES", hue="LIFESTAGE", data=lifestage_sales)
plt.title("Total Sales for Each Lifestage During the Entire Fiscal Year (1st July 2
plt.xlabel("Date")
plt.ylabel("Total Sales")
plt.legend(bbox_to_anchor=(1.01, 1), loc=2, borderaxespad=0.)
plt.show()
```



Like the holiday season statistics, we can see an increase in sales right before Christmas Day for all age demographics, except NEW FAMILIES, which remains consistent throughout the entire recorded duration. As new families are more inclined toward their careers and developing their newly established home, it's unlikely for them to spend on snack items frequently.

Let's see what sort of purchase behaviour each age demographic has!

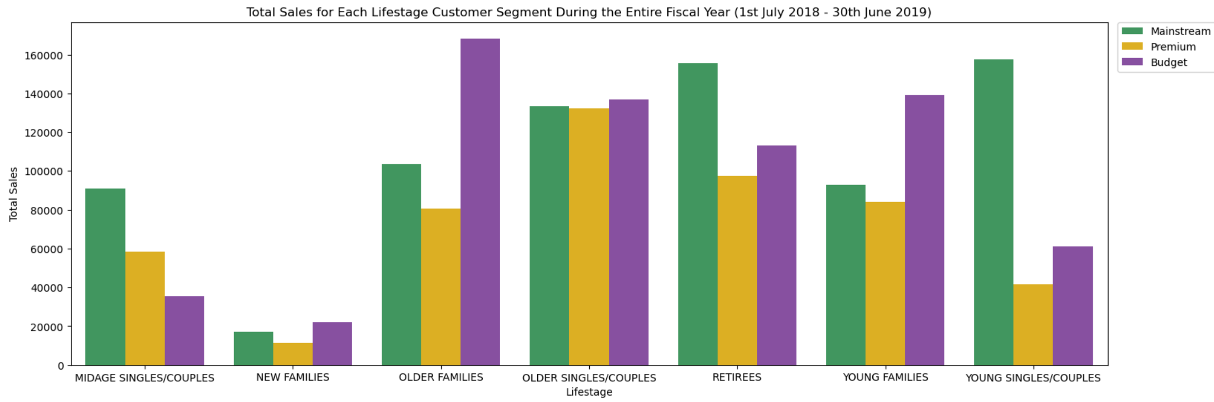
In [45]:
```
lifestage_segment=dataframe.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["TOT_SALES"]
lifestage_segment=lifestage_segment[lifestage_segment["LIFESTAGE"]!="None"] #   Rem
lifestage_segment=lifestage_segment.reset_index(drop=True)  #   Resetting the index
lifestage_segment
```

Out[45]:

	LIFESTAGE	PREMIUM_CUSTOMER	TOT_SALES
0	MIDAGE SINGLES/COUPLES	Mainstream	90803.85
1	MIDAGE SINGLES/COUPLES	Premium	58432.65
2	MIDAGE SINGLES/COUPLES	Budget	35514.80
3	NEW FAMILIES	Budget	21928.45
4	NEW FAMILIES	Mainstream	17013.90
5	NEW FAMILIES	Premium	11491.10
6	OLDER FAMILIES	Budget	168363.25
7	OLDER FAMILIES	Mainstream	103445.55
8	OLDER FAMILIES	Premium	80658.40
9	OLDER SINGLES/COUPLES	Budget	136769.80
10	OLDER SINGLES/COUPLES	Mainstream	133393.80
11	OLDER SINGLES/COUPLES	Premium	132263.15
12	RETIREES	Mainstream	155677.05
13	RETIREES	Budget	113147.80
14	RETIREES	Premium	97646.05
15	YOUNG FAMILIES	Budget	139345.85
16	YOUNG FAMILIES	Mainstream	92788.75
17	YOUNG FAMILIES	Premium	84025.50
18	YOUNG SINGLES/COUPLES	Mainstream	157621.60
19	YOUNG SINGLES/COUPLES	Budget	61141.60
20	YOUNG SINGLES/COUPLES	Premium	41642.10

In [55]:

```
#   Plotting a bar graph of the total sales for each lifestage and whether it is a


plt.figure(figsize=(18, 6))
sns.barplot(x="LIFESTAGE", y="TOT_SALES", hue="PREMIUM_CUSTOMER", data=lifestage_se
)
plt.title("Total Sales for Each Lifestage Customer Segment During the Entire Fiscal
plt.xlabel("Lifestage")
plt.ylabel("Total Sales")
plt.legend(bbox_to_anchor=(1.01, 1), loc=2, borderaxespad=0.)
plt.show()
```



In [47]:
```
lifestage_brands=dataframe.groupby(["LIFESTAGE", "BRAND_NAME", "PREMIUM_CUSTOMER",
lifestage_brands=lifestage_brands[lifestage_brands["LIFESTAGE"]!="None"]    #   Rem
lifestage_brands=lifestage_brands.reset_index(drop=True)    #   Resetting the index
midage=lifestage_brands[lifestage_brands["LIFESTAGE"]=="MIDAGE SINGLES/COUPLES"]
midage
```

Out[47]:

	LIFESTAGE	BRAND_NAME	PREMIUM_CUSTOMER	PROD_SIZE	TOT_SALES
0	MIDAGE SINGLES/COUPLES	Kettle	Mainstream	175	10557.0
1	MIDAGE SINGLES/COUPLES	Kettle	Mainstream	150	8381.2
2	MIDAGE SINGLES/COUPLES	Pringles	Mainstream	134	8177.0
3	MIDAGE SINGLES/COUPLES	Kettle	Premium	175	5815.8
4	MIDAGE SINGLES/COUPLES	Pringles	Premium	134	5538.9
...	...	...	...	...	...
133	MIDAGE SINGLES/COUPLES	Snbts	Mainstream	90	120.7
134	MIDAGE SINGLES/COUPLES	Cheezels	Budget	125	105.0
135	MIDAGE SINGLES/COUPLES	Sunbites	Mainstream	90	103.7
136	MIDAGE SINGLES/COUPLES	Sunbites	Budget	90	96.9
137	MIDAGE SINGLES/COUPLES	Woolworths	Budget	190	81.0

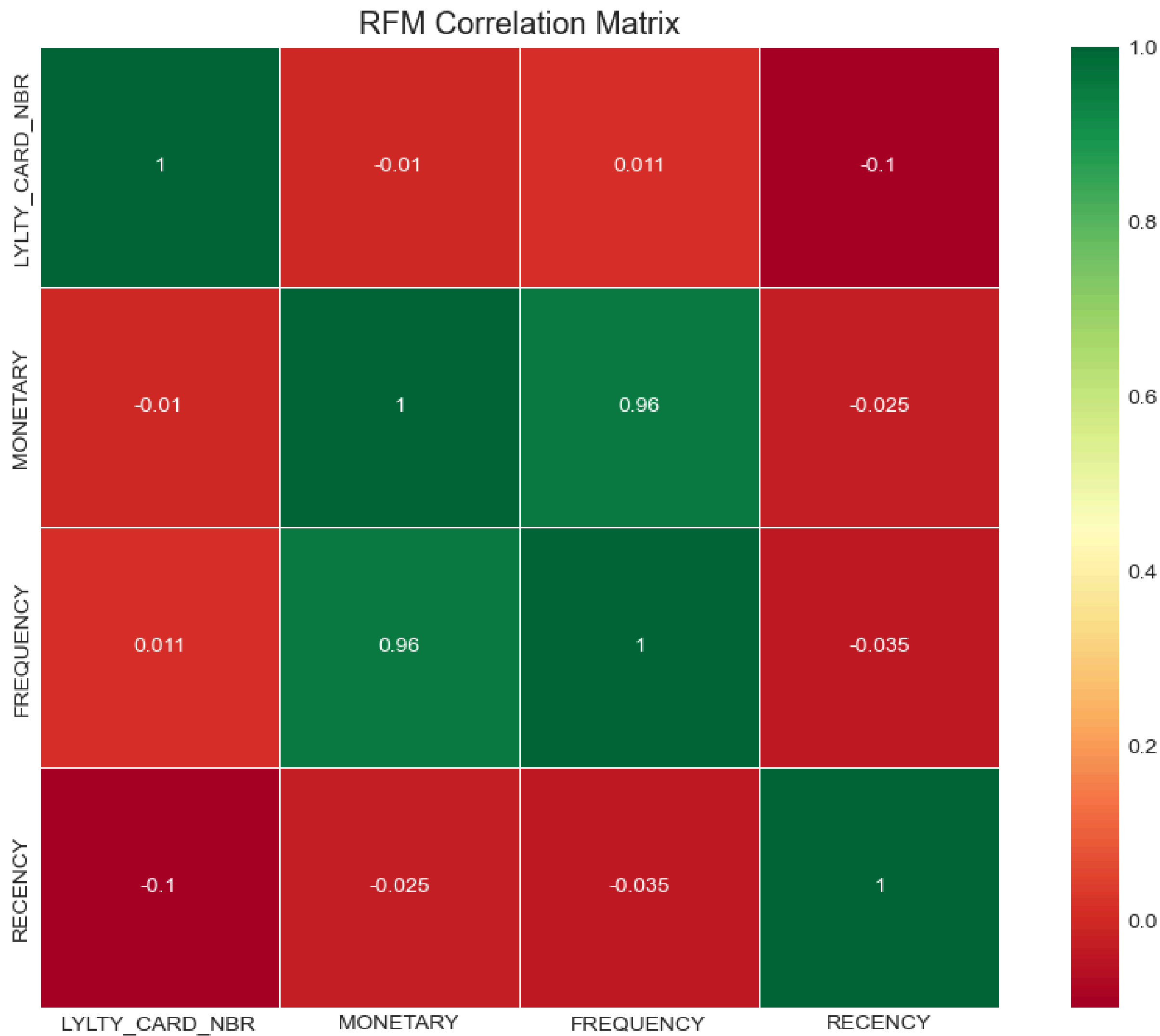
138 rows × 5 columns

With this, we can see that MIDAGE SINGLES/COUPLES prefer KETTLE® and 175 gramme package size the most in both the Mainstream and Premium customer segment.

Recency, Frequency and Monetary (RFM) Analysis:

Recency, Frequency and Monetary (RFM) analysis is a marketing technique used to quantitatively rank and group customers based on the recency, frequency and monetary total of their recent transactions to identify the best customers and perform targeted marketing campaigns. This can help us identify customers who are most valuable to the store, as well as those who may be at risk of churning.

In [86]:
```
#   Creating a new pandas.DataFrame with the Recency, Frequency and Monetary (RFM)

rfm=dataframe.groupby("LYLTY_CARD_NBR")["TOT_SALES"].agg(["sum", "count"]).reset_in
rfm.columns=["LYLTY_CARD_NBR", "MONETARY", "FREQUENCY"] #   Renaming the columns of
rfm["RECENCY"]=(datetime.datetime.strptime("2019-06-30", "%Y-%m-%d")-dataframe.grou
rfm=rfm.dropna()    #   Dropping the null values from the pandas.DataFrame.
rfm=rfm.reset_index(drop=True)  #   Resetting the index of the pandas.DataFrame.

# Create a heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(rfm.corr(), annot=True, cmap="RdYlGn", square=True, linewidths=0.5, lin
plt.title("RFM Correlation Matrix")
plt.show()
```



From the Recency, Frequency and Monetary (RFM) analysis, there don't seem to be many customers at risk of churning, but the scatter graph does suggest that the oldest customers may be most valuable to the store and the recent ones may likely be at risk of churning.

Insights from Sales Data Analysis

Holiday Season Sales

- Sales gradually increase during the holiday season, peaking on **December 24th**, and then drop suddenly after Christmas Day.
- Ideal time for **promotional campaigns or discounts** is during this period.

Product Sales

- **380g package size** is the highest-selling during the holiday season.

- **KETTLE®** is the highest-selling brand during both the holiday season and the entire year.
- **175g package size** is the highest-selling on average throughout the year, with a significant lead (**37%**) over the second highest-selling size.

Customer Loyalty

- **OLDER SINGLES/COUPLES** are the most loyal customers.
- **NEW FAMILIES** are the least loyal customers.

Customer Purchasing Behavior

- **MIDAGE SINGLES/COUPLES**:
  - Have the highest **Mainstream and Premium purchases**.
  - Prefer **KETTLE® and 175g package size** in both Mainstream and Premium segments.

Customer Value

- Oldest customers may be the most **valuable** to the store.
- Recent customers may be at risk of **churning**.

In [ ]:

```
```