```
#Import some libraries to perform some calculations, visualization, plotting, remove warnings and other usage of functions

import pandas as pd
import matplotlib.pyplot as plt
import seaborn  as sns
import sklearn
import numpy as np
import datetime as dt
import math
import scipy as sp
import scipy.stats as stats
import warnings
warnings.filterwarnings("ignore")
```

Customer Demography

```
#Load the customer demography dataset of KPMG and stored in variable called demo:

demo = pd.read_csv("/content/Cus_Demography.csv - Sheet1.csv")
demo
```

	customer_id	first_name	last_name	gender	past_3_years_bike_related_purchases	DOB	job_title	job_industry_category	wealth_segment	deceased_indicator	
0	1	Laraine	Medendorp	F	93	1953-10-12	Executive Secretary	Health	Mass Customer	N	
1	2	Eli	Bockman	Male	81	1980-12-16	Administrative Officer	Financial Services	Mass Customer	N	<script>a
2	3	Arlin	Dearle	Male	61	1954-01-20	Recruiting Manager	Property	Mass Customer	N	
3	4	Talbot	NaN	Male	33	1961-10-03	NaN	IT	Mass Customer	N	() { _; } /tr
4	5	Sheila-kathryn	Calton	Female	56	1977-05-13	Senior Editor	NaN	Affluent Customer	N	
...	...	...	...	...	...	...	...	...	...	...	
3995	3996	Rosalia	Halgarth	Female	8	1975-08-09	VP Product Management	Health	Mass Customer	N	
3996	3997	Blanch	Nisuis	Female	87	2001-07-13	Statistician II	Manufacturing	High Net Worth	N	
3997	3998	Sarene	Woolley	U	60	NaN	Assistant Manager	IT	High Net Worth	N	
3998	3999	Patrizius	NaN	Male	11	1973-10-24	NaN	Manufacturing	Affluent Customer	N	Â¡â¢Â£Âº
3999	4000	Kippy	Oldland	Male	76	1991-11-05	Software Engineer IV	NaN	Affluent Customer	N	

4000 rows × 13 columns

```
#This command gives the information of demography dataset:

demo.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4000 entries, 0 to 3999
Data columns (total 13 columns):
 #   Column                               Non-Null Count  Dtype  
---  ------                               --------------  -----  
 0   customer_id                          4000 non-null   int64  
 1   first_name                           4000 non-null   object 
 2   last_name                            3875 non-null   object 
 3   gender                               4000 non-null   object 
 4   past_3_years_bike_related_purchases  4000 non-null   int64  
 5   DOB                                  3913 non-null   object 
 6   job_title                            3494 non-null   object 
 7   job_industry_category                3344 non-null   object 
 8   wealth_segment                       4000 non-null   object 
 9   deceased_indicator                   4000 non-null   object 
 10  default                              3698 non-null   object 
 11  owns_car                             4000 non-null   object 
 12  tenure                               3913 non-null   float64
dtypes: float64(1), int64(2), object(10)
memory usage: 406.4+ KB
```

```
#This command gives the static information of demography dataset:

demo.describe()
```

	customer_id	past_3_years_bike_related_purchases	tenure
count	4000.000000	4000.000000	3913.000000
mean	2000.500000	48.890000	10.657041
std	1154.844867	28.715005	5.660146
min	1.000000	0.000000	1.000000
25%	1000.750000	24.000000	6.000000
50%	2000.500000	48.000000	11.000000
75%	3000.250000	73.000000	15.000000
max	4000.000000	99.000000	22.000000

```
#This command shows the order pair of demography dataset:

demo.shape
```

```
(4000, 13)
```

```
#This command shows the columns of demography dataset:

demo.columns
```

```
Index(['customer_id', 'first_name', 'last_name', 'gender',
       'past_3_years_bike_related_purchases', 'DOB', 'job_title',
       'job_industry_category', 'wealth_segment', 'deceased_indicator',
```

```
            'default', 'owns_car', 'tenure'],
           dtype='object')
```

```
#This command gives the duplicated values  of demography dataset:

demo.duplicated().sum()
```

```
0
```

```
#This command gives the missing values of demography dataset:

demo.isnull().sum()
```

```
customer_id                            0
first_name                             0
last_name                            125
gender                                 0
past_3_years_bike_related_purchases    0
DOB                                   87
job_title                            506
job_industry_category                656
wealth_segment                         0
deceased_indicator                     0
default                              302
owns_car                               0
tenure                                87
dtype: int64
```

```
#This command Drops the missing values:

demo.dropna(inplace = True)
demo.isnull().sum()
```

```
customer_id                          0
first_name                           0
last_name                            0
gender                               0
past_3_years_bike_related_purchases  0
DOB                                  0
job_title                            0
job_industry_category                0
wealth_segment                       0
deceased_indicator                   0
default                              0
owns_car                             0
tenure                               0
dtype: int64
```

```
#This command shows the order pair of demography dataset after dropping missing rows:

demo.shape
```

```
(2630, 13)
```

```
#This command counts the value of deceased_indicator column:

demo.deceased_indicator.value_counts()
```

```
N    2628
Y       2
Name: deceased_indicator, dtype: int64
```

```
#This command drops some columns:

demo.drop(['first_name', 'last_name', 'default', 'job_title', 'deceased_indicator'], axis=1, inplace=True)
```

```
#This command shows the order pair of demography dataset after dropping some columns:

demo.shape
```

```
(2630, 8)
```

```
#This command shows the first 5 rows of demography dataset:

demo.head()
```

	customer_id	gender	past_3_years_bike_related_purchases	DOB	job_industry_category	wealth_segment	owns_car	tenure
0	1	F	93	1953-10-12	Health	Mass Customer	Yes	11.0
1	2	Male	81	1980-12-16	Financial Services	Mass Customer	Yes	16.0
2	3	Male	61	1954-01-20	Property	Mass Customer	Yes	15.0
8	9	Female	97	1973-03-10	Argiculture	Affluent Customer	Yes	8.0
9	10	Female	49	1988-10-11	Financial Services	Mass Customer	Yes	20.0

```
#This command counts the value of gender column:

demo.gender.value_counts()
```

```
Female    1366
Male      1262
F            1
Femal        1
Name: gender, dtype: int64
```

```
#This command replace some values in gender column:

demo['gender'].replace({'F' : 'Female'}, inplace=True)
demo['gender'].replace({'Femal' : 'Female'}, inplace=True)
```

```
#This command counts the value of gender column after editing:

demo.gender.value_counts()
```

```
Female    1368
Male      1262
Name: gender, dtype: int64
```

```
#This command counts the value of DOB column:

demo.DOB.value_counts
```

```
<bound method IndexOpsMixin.value_counts of 0       1953-10-12
1       1980-12-16
2       1954-01-20
8       1973-03-10
9       1988-10-11
           ...
3992    1974-12-05
3993    1989-04-07
3994    1975-12-12
3995    1975-08-09
3996    2001-07-13
Name: DOB, Length: 2630, dtype: object>
```

```
#This command converts DOB column into age and create new age column:

demo['DOB'] = pd.to_datetime(demo['DOB'])
demo['age'] = (dt.datetime.now() - demo['DOB']) / np.timedelta64(1, 'Y')
```

```
#This command counts the value of age column:

demo.age.value_counts
```

```
<bound method IndexOpsMixin.value_counts of 0       70.149663
1       42.970460
2       69.875872
8       50.740640
9       35.150997
          ...
3992    49.002069
3993    34.663650
3994    47.983568
3995    48.325806
3996    22.397827
Name: age, Length: 2630, dtype: float64>
```

```
#This command givs the minimum and maximum value of age column:

print(demo['age'].min(), demo['age'].max())
```

```
21.73799103021743 92.12136645887101
```

```
#Following command create age_group column for calculation purpose:

ag = pd.Series(['20-34','35-49', '50-64', '65-79', '80-94'], dtype='category')
demo['age_group'] = ag

demo.loc[demo['age']<=34, 'age_group'] = ag[0]
demo.loc[(demo['age']>34) & (demo['age']<=49), 'age_group'] = ag[1]
demo.loc[(demo['age']>49) & (demo['age']<=64), 'age_group'] = ag[2]
demo.loc[(demo['age']>64) & (demo['age']<=79), 'age_group'] = ag[3]
demo.loc[demo['age']>79, 'age_group'] = ag[4]

#This command shows the information for demography dataset:
print(demo.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2630 entries, 0 to 3996
Data columns (total 10 columns):
 #   Column                               Non-Null Count  Dtype
---  ------                               --------------  -----
 0   customer_id                          2630 non-null   int64
 1   gender                               2630 non-null   object
 2   past_3_years_bike_related_purchases  2630 non-null   int64
 3   DOB                                  2630 non-null   datetime64[ns]
 4   job_industry_category                2630 non-null   object
 5   wealth_segment                       2630 non-null   object
 6   owns_car                             2630 non-null   object
 7   tenure                               2630 non-null   float64
 8   age                                  2630 non-null   float64
 9   age_group                            2630 non-null   category
dtypes: category(1), datetime64[ns](1), float64(2), int64(2), object(4)
memory usage: 208.2+ KB
None
```

```
#This command gives first 5 rows of demography dataset:

demo.head()
```

	customer_id	gender	past_3_years_bike_related_purchases	DOB	job_industry_category	wealth_segment	owns_car	tenure	age	age_group
0	1	Female	93	1953-10-12	Health	Mass Customer	Yes	11.0	70.149663	65-79
1	2	Male	81	1980-12-16	Financial Services	Mass Customer	Yes	16.0	42.970460	35-49
2	3	Male	61	1954-01-20	Property	Mass Customer	Yes	15.0	69.875872	65-79
8	9	Female	97	1973-03-10	Argiculture	Affluent Customer	Yes	8.0	50.740640	50-64
9	10	Female	49	1988-10-11	Financial Services	Mass Customer	Yes	20.0	35.150997	35-49

Customer Address

```
#Load the Customer Address dataset of KPMG and stored in variable called addr:

addr = pd.read_csv("/content/Cus_Address.csv - Sheet1.csv")
addr
```

	customer_id	address	postcode	state	country	property_valuation
0	1	060 Morning Avenue	2016	New South Wales	Australia	10
1	2	6 Meadow Vale Court	2153	New South Wales	Australia	10
2	4	0 Holy Cross Court	4211	QLD	Australia	9

```
#This command shows the information of address dataset:

addr.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3999 entries, 0 to 3998
Data columns (total 6 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   customer_id         3999 non-null   int64 
 1   address             3999 non-null   object
 2   postcode            3999 non-null   int64 
 3   state               3999 non-null   object
 4   country             3999 non-null   object
 5   property_valuation  3999 non-null   int64 
dtypes: int64(3), object(3)
memory usage: 187.6+ KB
```

```
#This command shows the Static values of address dataset:

addr.describe()
```

	customer_id	postcode	property_valuation
count	3999.000000	3999.000000	3999.000000
mean	2003.987997	2985.755939	7.514379
std	1154.576912	844.878364	2.824663
min	1.000000	2000.000000	1.000000
25%	1004.500000	2200.000000	6.000000
50%	2004.000000	2768.000000	8.000000
75%	3003.500000	3750.000000	10.000000
max	4003.000000	4883.000000	12.000000

```
#This command shows the order pair of address dataset:

addr.shape
```

```
(3999, 6)
```

```
#This command shows the columns of address dataset:

addr.columns
```

```
Index(['customer_id', 'address', 'postcode', 'state', 'country',
       'property_valuation'],
      dtype='object')
```

```
#This command calculate the duplicate values of address dataset:

addr.duplicated().sum()
```

```
0
```

```
#This command calculate the missing values of address dataset:

addr.isnull().sum()
```

```
customer_id           0
address               0
postcode              0
state                 0
country               0
property_valuation    0
dtype: int64
```

```
#This command counts the value of state column:

addr.state.value_counts()
```

```
NSW               2054
VIC                939
QLD                838
New South Wales     86
Victoria            82
Name: state, dtype: int64
```

```
#This command replace some values in state column:

addr['state'].replace({'New South Wales' : 'NSW'}, inplace=True)
addr['state'].replace({'Victoria' : 'VIC'}, inplace=True)
```

```
#This command counts the value of state column:

addr.state.value_counts()
```

```
NSW    2140
VIC    1021
QLD     838
Name: state, dtype: int64
```

```
#This command shows the first 5 rows of adreess dataset:

addr.head()
```

	customer_id	address	postcode	state	country	property_valuation
0	1	060 Morning Avenue	2016	NSW	Australia	10

Customer Transaction

```
#Load the Customer Transaction dataset of KPMG and stored in variable called trans:

trans = pd.read_csv("/content/Transaction.csv - Sheet1.csv")
trans
```

	customer_id	transaction_date	online_order	order_status	brand	product_line	product_class	product_size	list_price	standard_cost	product_first_sold_date
0	2950	2/25/2017	False	Approved	Solex	Standard	medium	medium	71.49	$53.62	41245.0
1	3120	5/21/2017	True	Approved	Trek Bicycles	Standard	medium	large	2091.47	$388.92	41701.0
2	402	10/16/2017	False	Approved	OHM Cycles	Standard	low	medium	1793.43	$248.82	36361.0
3	3135	8/31/2017	False	Approved	Norco Bicycles	Standard	medium	medium	1198.46	$381.10	36145.0
4	787	10/1/2017	True	Approved	Giant Bicycles	Standard	medium	large	1765.30	$709.48	42226.0
...	...	...	...	...	...	...	...	...	...	...	...
19995	1018	6/24/2017	True	Approved	OHM Cycles	Standard	high	medium	2005.66	$1,203.40	37823.0
19996	127	11/9/2017	True	Approved	Solex	Road	medium	medium	416.98	$312.74	35560.0
19997	2284	4/14/2017	True	Approved	OHM	Standard	medium	medium	1636.90	$44.71	40410.0

```
#This command give the information of transaction dataset:

trans.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 11 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   customer_id              20000 non-null  int64  
 1   transaction_date         20000 non-null  object 
 2   online_order             19640 non-null  object 
 3   order_status             20000 non-null  object 
 4   brand                    19803 non-null  object 
 5   product_line             19803 non-null  object 
 6   product_class            19803 non-null  object 
 7   product_size             19803 non-null  object 
 8   list_price               20000 non-null  float64
 9   standard_cost            19803 non-null  object 
 10  product_first_sold_date  19803 non-null  float64
dtypes: float64(2), int64(1), object(8)
memory usage: 1.7+ MB
```

```
#This command gives the static values of transaction dataset:

trans.describe()
```

	customer_id	list_price	product_first_sold_date
count	20000.000000	20000.000000	19803.000000
mean	1738.246050	1107.829449	38199.776549
std	1011.951046	582.825242	2875.201110
min	1.000000	12.010000	33259.000000
25%	857.750000	575.270000	35667.000000
50%	1736.000000	1163.890000	38216.000000
75%	2613.000000	1635.300000	40672.000000
max	5034.000000	2091.470000	42710.000000

```
#This command shows the order pair of transaction dataset:

trans.shape
```

```
(20000, 11)
```

```
#This command shows the column of transaction dataset:

trans.columns
```

```
Index(['customer_id', 'transaction_date', 'online_order', 'order_status',
       'brand', 'product_line', 'product_class', 'product_size', 'list_price',
       'standard_cost', 'product_first_sold_date'],
      dtype='object')
```

```
#This command calculate dupliate values of transaction dataset:

trans.duplicated().sum()
```

```
0
```

```
#This command calculate mising values of transaction dataset:

trans.isnull().sum()
```

```
customer_id                 0
transaction_date            0
online_order              360
order_status                0
brand                     197
product_line              197
product_class             197
product_size              197
list_price                  0
standard_cost             197
product_first_sold_date   197
dtype: int64
```

```
trans = trans.query("order_status == ['Approved']")
```

```
#This command drops the missing values in trasaction dataset:

trans.dropna(inplace = True)
trans.isnull().sum()
```

```
customer_id               0
transaction_date          0
online_order              0
order_status              0
brand                     0
product_line              0
product_class             0
product_size              0
list_price                0
standard_cost             0
product_first_sold_date   0
dtype: int64
```

```
#This command shows the order pair of transaction dataset after drops missing rows:

trans.shape
```

```
(19273, 11)
```

```
#This command counts value in product_first_sold_date column:

trans.product_first_sold_date.value_counts()
```

```
33879.0    228
41064.0    222
37823.0    219
39880.0    218
38482.0    214
           ...
42404.0    166
41848.0    166
41922.0    161
37659.0    160
34586.0    157
Name: product_first_sold_date, Length: 100, dtype: int64
```

```
#This command change product_first_sold_date datatype:

trans['product_first_sold_date'] = pd.to_datetime(trans['product_first_sold_date'], unit='s')
```

```
#This command shows the value of trans.product_first_sold_date column:

trans.product_first_sold_date
```

```
0       1970-01-01 11:27:25
1       1970-01-01 11:35:01
2       1970-01-01 10:06:01
3       1970-01-01 10:02:25
4       1970-01-01 11:43:46
                   ...
19995   1970-01-01 10:30:23
19996   1970-01-01 09:52:40
19997   1970-01-01 11:13:30
19998   1970-01-01 10:36:56
19999   1970-01-01 10:05:34
Name: product_first_sold_date, Length: 19273, dtype: datetime64[ns]
```

```
#This command counts the value of standard_cost column:

trans.standard_cost.value_counts()
```

```
$388.92        456
$954.82        387
$53.62         268
$161.60        229
$260.14        228
               ...
$151.96        123
$206.35        111
312.7350159      1
270.2999878      1
667.4000244      1
Name: standard_cost, Length: 103, dtype: int64
```

```
#this command gives the data type of standard_cost column:

print(trans['standard_cost'].dtypes)
```

```
object
```

```
#thus command is used to modify the attributes in standard_cost column:

trans['standard_cost'] = trans['standard_cost'].str.replace(',', '').str.replace('$', '').astype(float).round(decimals = 2)
```

```
#thus command is used to modify the attributes in list_price column:

trans['list_price'] = trans['list_price'].replace('$', '').round(decimals = 2)
```

```
#this command gives the data type of standard_cost column and list_price column:

print("D-type of list_price is: ", trans['list_price'].dtype)
print("D-type of Standard_cost is: ",trans['standard_cost'].dtype)
```

```
D-type of list_price is:  float64
D-type of Standard_cost is:  float64
```

```
#This command is used for creating profit column in transaction dataset:

trans['profit'] = trans['list_price'] - trans['standard_cost']
```

```
#This command is used to show first 5 rows of transaction dataset:

trans.head()
```

	customer_id	transaction_date	online_order	order_status	brand	product_line	product_class	product_size	list_price	standard_cost	product_first_sold_date	profit
0	2950	2/25/2017	False	Approved	Solex	Standard	medium	medium	71.49	53.62	1970-01-01 11:27:25	17.87
1	3120	5/21/2017	True	Approved	Trek Bicycles	Standard	medium	large	2091.47	388.92	1970-01-01 11:35:01	1702.55
2	402	10/16/2017	False	Approved	OHM Cycles	Standard	low	medium	1793.43	248.82	1970-01-01 10:06:01	1544.61
3	3135	8/31/2017	False	Approved	Norco Bicycles	Standard	medium	medium	1198.46	381.10	1970-01-01 10:02:25	817.36

```
#This command is used to modify datatype of transaction_date column:

trans['transaction_date'] = pd.to_datetime(trans['transaction_date'])
```

```
#The cammand is used to create column called recency in transaction dataset:

trans['recency'] = (trans['transaction_date'].max() - trans['transaction_date']) / np.timedelta64(1,'D')

#The couple of line of cammand is used to create a dataset called rfm_df:
rfm_df = trans.groupby('customer_id').aggregate({'recency':'min', 'customer_id':'count', 'profit':'sum'})

rfm_df.rename(columns={'customer_id':'frequency'}, inplace=True)
```

```
#This command shows the first 5 rows of rfm_df dataset:

rfm_df.head()
```

customer_id	recency	frequency	profit
1	7.0	11	3018.09
2	128.0	3	2226.26
3	102.0	7	3290.21
4	195.0	2	220.57
5	16.0	6	2394.94

```
#This command is used to create r, f, m column in rfm_df dataset:
# Create R, F and M score columns
# A scale of 1 - 4 was used
# 4 for quartiles [0, 0.25, 0.50, 0.75, 1]

rfm_df['r'] = pd.qcut(rfm_df['recency'], q=4, labels=[4, 3, 2, 1])
rfm_df['f'] = pd.qcut(rfm_df['frequency'], q=4, labels=[1, 2, 3, 4])
rfm_df['m'] = pd.qcut(rfm_df['profit'], q=4, labels=[1, 2, 3, 4])

rfm_df.head()
```

customer_id	recency	frequency	profit	r	f	m
1	7.0	11	3018.09	4	4	3
2	128.0	3	2226.26	1	1	2
3	102.0	7	3290.21	1	3	3
4	195.0	2	220.57	1	1	1
5	16.0	6	2394.94	4	3	2

```
#This command is used to create rfm_score column based on r, f, m values:

rfm_df['rfm_score'] = 100*rfm_df['r'].astype(int) + 10*rfm_df['f'].astype(int) + rfm_df['m'].astype(int)
rfm_df.head()
```

customer_id	recency	frequency	profit	r	f	m	rfm_score
1	7.0	11	3018.09	4	4	3	443
2	128.0	3	2226.26	1	1	2	112
3	102.0	7	3290.21	1	3	3	133
4	195.0	2	220.57	1	1	1	111
5	16.0	6	2394.94	4	3	2	432

```
#This command is used to show the datatype of rfm_score column:

rfm_df.rfm_score.dtype
```

```
dtype('int64')
```

```
#This command is used to create a customer_profile column based on rfm_score column:

rfm_df['customer_profile'] = pd.qcut(rfm_df['rfm_score'], q=4, labels=['Bronze', 'Silver', 'Gold', 'Platinum'])
```

```
#This command gives the information and as well as first 5 rows of rfm_df dataset:

print(rfm_df.info())
rfm_df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3490 entries, 1 to 5034
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype   
---  ------           --------------  -----   
 0   recency          3490 non-null   float64 
 1   frequency        3490 non-null   int64   
 2   profit           3490 non-null   float64 
 3   r                3490 non-null   category
 4   f                3490 non-null   category
 5   m                3490 non-null   category
 6   rfm_score        3490 non-null   int64   
 7   customer_profile 3490 non-null   category
dtypes: category(4), float64(2), int64(2)
memory usage: 150.8 KB
```

```
#This command gives the first 5 rows of transaction dataset:

trans.head()
```

	customer_id	transaction_date	online_order	order_status	brand	product_line	product_class	product_size	list_price	standard_cost	product_first_sold_date	profit	r
0	2950	2017-02-25	False	Approved	Solex	Standard	medium	medium	71.49	53.62	1970-01-01 11:27:25	17.87	
1	3120	2017-05-21	True	Approved	Trek Bicycles	Standard	medium	large	2091.47	388.92	1970-01-01 11:35:01	1702.55	
2	402	2017-10-16	False	Approved	OHM Cycles	Standard	low	medium	1793.43	248.82	1970-01-01 10:06:01	1544.61	
3	3135	2017-08-31	False	Approved	Norco Bicycles	Standard	medium	medium	1198.46	381.10	1970-01-01 10:02:25	817.36	
4	787	2017-10-01	True	Approved	Giant Bicycles	Standard	medium	large	1765.30	709.48	1970-01-01 11:43:46	1055.82	

Merge dataset

```
#This command create a dataset called "dataset" based on uper 4 datasets:
# Join Customer Demographic, Customer Address and RFM score dataframes on customer id:

dataset = rfm_df.merge(addr.merge(demo, how='inner', on='customer_id'), how='inner', on='customer_id')

print(dataset.info())
dataset.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2325 entries, 0 to 2324
Data columns (total 23 columns):
 #   Column                               Non-Null Count  Dtype         
---  ------                               --------------  -----         
 0   customer_id                          2325 non-null   int64         
 1   recency                              2325 non-null   float64       
 2   frequency                            2325 non-null   int64         
 3   profit                               2325 non-null   float64       
 4   r                                    2325 non-null   category      
 5   f                                    2325 non-null   category      
 6   m                                    2325 non-null   category      
 7   rfm_score                            2325 non-null   int64         
 8   customer_profile                     2325 non-null   category      
 9   address                              2325 non-null   object        
 10  postcode                             2325 non-null   int64         
 11  state                                2325 non-null   object        
 12  country                              2325 non-null   object        
 13  property_valuation                   2325 non-null   int64         
 14  gender                               2325 non-null   object        
 15  past_3_years_bike_related_purchases  2325 non-null   int64         
 16  DOB                                  2325 non-null   datetime64[ns]
 17  job_industry_category                2325 non-null   object        
 18  wealth_segment                       2325 non-null   object        
 19  owns_car                             2325 non-null   object        
 20  tenure                               2325 non-null   float64       
 21  age                                  2325 non-null   float64       
 22  age_group                            2325 non-null   category      
dtypes: category(5), datetime64[ns](1), float64(4), int64(6), object(7)
memory usage: 357.5+ KB
None
```

	customer_id	recency	frequency	profit	r	f	m	rfm_score	customer_profile	address	...	property_valuation	gender	past_3_years_bike_related_purchases	DOB	job_i
0	1	7.0	11	3018.09	4	4	3	443	Platinum	060 Morning Avenue	...	10	Female	93	1953-10-12	
1	2	128.0	3	2226.26	1	1	2	112	Bronze	6 Meadow Vale Court	...	10	Male	81	1980-12-16	
2	9	78.0	6	2353.11	2	3	2	232	Silver	97736 7th Trail	...	12	Female	97	1973-03-10	
3	12	67.0	7	3540.03	2	3	3	233	Silver	44339 Golden Leaf Alley	...	4	Male	58	1994-07-21	
4	13	27.0	7	4337.38	3	3	4	334	Gold	2 Sutherland Street	...	6	Male	38	1955-02-15	

5 rows × 23 columns

```
#This command is used to convert and as well as save the dataset:

dataset.to_csv('dataset.csv', index=False)
```

```
#This command gives the order pair of dataset:

dataset.shape
```

```
(2325, 23)
```

```
#This command gives the information of dataset:

dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2325 entries, 0 to 2324
Data columns (total 23 columns):
 #   Column                               Non-Null Count  Dtype         
```

```
---  ------                                --------------  -----
 0   customer_id                           2325 non-null   int64
 1   recency                               2325 non-null   float64
 2   frequency                             2325 non-null   int64
 3   profit                                2325 non-null   float64
 4   r                                     2325 non-null   category
 5   f                                     2325 non-null   category
 6   m                                     2325 non-null   category
 7   rfm_score                             2325 non-null   int64
 8   customer_profile                      2325 non-null   category
 9   address                               2325 non-null   object
 10  postcode                              2325 non-null   int64
 11  state                                 2325 non-null   object
 12  country                               2325 non-null   object
 13  property_valuation                    2325 non-null   int64
 14  gender                                2325 non-null   object
 15  past_3_years_bike_related_purchases   2325 non-null   int64
 16  DOB                                   2325 non-null   datetime64[ns]
 17  job_industry_category                 2325 non-null   object
 18  wealth_segment                        2325 non-null   object
 19  owns_car                              2325 non-null   object
 20  tenure                                2325 non-null   float64
 21  age                                   2325 non-null   float64
 22  age_group                             2325 non-null   category
dtypes: category(5), datetime64[ns](1), float64(4), int64(6), object(7)
memory usage: 357.5+ KB
```

```
#This command gives the static values of dataset:

dataset.describe()
```

	customer_id	recency	frequency	profit	rfm_score	postcode	property_valuation	past_3_years_bike_related_purchases	tenure	age
count	2325.000000	2325.000000	2325.000000	2325.000000	2325.000000	2325.000000	2325.000000	2325.000000	2325.000000	2325.000000
mean	1724.224516	62.974194	5.523871	3047.687140	277.354409	2987.420645	7.513978	49.209462	10.739355	46.129479
std	1010.355330	60.104336	2.262080	1770.657023	116.677347	857.273903	2.823463	28.626828	5.683114	12.443453
min	1.000000	0.000000	1.000000	15.080000	111.000000	2000.000000	1.000000	0.000000	1.000000	21.737991
25%	842.000000	18.000000	4.000000	1774.120000	211.000000	2193.000000	6.000000	25.000000	6.000000	36.634943
50%	1720.000000	45.000000	5.000000	2770.850000	311.000000	2766.000000	8.000000	48.000000	11.000000	46.206666
75%	2592.000000	88.000000	7.000000	4067.640000	411.000000	3752.000000	10.000000	73.000000	16.000000	55.208904
max	3497.000000	353.000000	14.000000	11668.950000	444.000000	4883.000000	12.000000	99.000000	22.000000	92.121366

```
#This command shows the columns of dataset:

dataset.columns
```

```
Index(['customer_id', 'recency', 'frequency', 'profit', 'r', 'f', 'm',
       'rfm_score', 'customer_profile', 'address', 'postcode', 'state',
       'country', 'property_valuation', 'gender',
       'past_3_years_bike_related_purchases', 'DOB', 'job_industry_category',
       'wealth_segment', 'owns_car', 'tenure', 'age', 'age_group'],
      dtype='object')
```

```
#This command calculates the duplicate values of dataset:

dataset.duplicated().sum()
```

```
0
```

```
#This command goves the missing values of dataset if there is:

dataset.isnull().sum()
```

```
customer_id                           0
recency                               0
frequency                             0
profit                                0
r                                     0
f                                     0
m                                     0
rfm_score                             0
customer_profile                      0
address                               0
postcode                              0
state                                 0
country                               0
property_valuation                    0
gender                                0
past_3_years_bike_related_purchases   0
DOB                                   0
job_industry_category                 0
wealth_segment                        0
owns_car                              0
tenure                                0
age                                   0
age_group                             0
dtype: int64
```

```
#This command counts the gender column:

dataset.gender.value_counts()
```

```
Female    1187
Male      1138
Name: gender, dtype: int64
```

New Customer List

```
#Load the New_1000_Customer_List dataset of KPMG and stored in variable called new_c:

new_c = pd.read_csv("/content/Cus_Newlist.csv - Sheet1.csv")
new_c
```

	first_name	last_name	gender	past_3_years_bike_related_purchases	DOB	job_title	job_industry_category	wealth_segment	deceased_indicator	owns_car	...	stat
0	Chickie	Brister	Male	86	1957-07-12	General Manager	Manufacturing	Mass Customer	N	Yes	...	QL
1	Morly	Genery	Male	69	1970-03-22	Structural Engineer	Property	Mass Customer	N	No	...	NSV
2	Ardelis	Forrester	Female	10	1974-08-28	Senior Cost Accountant	Financial Services	Affluent Customer	N	No	...	VI
3	Lucine	Stutt	Female	64	1979-01-28	Account Representative III	Manufacturing	Affluent Customer	N	Yes	...	QL
4	Melinda	Hadlee	Female	34	1965-09-21	Financial Analyst	Financial Services	Affluent Customer	N	No	...	NSV
...	...	...	...	...	...	...	...	...	...	...	...	
995	Ferdinand	Romanetti	Male	60	1959-10-07	Paralegal	Financial Services	Affluent Customer	N	No	...	NSV
996	Burk	Wortley	Male	22	2001-10-17	Senior Sales Associate	Health	Mass Customer	N	No	...	NSV
997	Melloney	Temby	Female	17	1954-10-05	Budget/Accounting Analyst IV	Financial Services	Affluent Customer	N	Yes	...	QL

```
#This command gives the information of new_cut_list dataset:

new_c.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 23 columns):
 #   Column                               Non-Null Count  Dtype  
---  ------                               --------------  -----  
 0   first_name                           1000 non-null   object 
 1   last_name                            971 non-null    object 
 2   gender                               1000 non-null   object 
 3   past_3_years_bike_related_purchases  1000 non-null   int64  
 4   DOB                                  983 non-null    object 
 5   job_title                            894 non-null    object 
 6   job_industry_category                835 non-null    object 
 7   wealth_segment                       1000 non-null   object 
 8   deceased_indicator                   1000 non-null   object 
 9   owns_car                             1000 non-null   object 
 10  tenure                               1000 non-null   int64  
 11  address                              1000 non-null   object 
 12  postcode                             1000 non-null   int64  
 13  state                                1000 non-null   object 
 14  country                              1000 non-null   object 
 15  property_valuation                   1000 non-null   float64
 16  Unnamed: 16                          1000 non-null   float64
 17  Unnamed: 17                          1000 non-null   float64
 18  Unnamed: 18                          1000 non-null   float64
 19  Unnamed: 19                          1000 non-null   float64
 20  Unnamed: 20                          1000 non-null   object 
 21  Rank                                 1000 non-null   int64  
 22  Value                                1000 non-null   float64
dtypes: float64(6), int64(4), object(13)
memory usage: 179.8+ KB
```

```
#This command gives the static values of new_cut_list dataset:

new_c.describe()
```

	past_3_years_bike_related_purchases	tenure	postcode	property_valuation	Unnamed: 16	Unnamed: 17	Unnamed: 18	Unnamed: 19	Rank	Value
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000
mean	49.836000	11.388000	3019.227000	7.397000	0.743200	0.833737	0.937824	0.866467	498.819000	0.881714
std	27.796686	5.037145	848.895767	2.758804	0.211594	0.253637	0.305892	0.291796	288.810997	0.293525
min	0.000000	0.000000	2000.000000	1.000000	0.400000	0.400000	0.400000	0.340000	1.000000	0.340000
25%	26.750000	7.000000	2209.000000	6.000000	0.560000	0.612500	0.700000	0.630000	250.000000	0.649531
50%	51.000000	11.000000	2800.000000	8.000000	0.730000	0.820000	0.900000	0.839375	500.000000	0.860000
75%	72.000000	15.000000	3845.500000	9.000000	0.930000	1.010000	1.140625	1.062500	750.250000	1.075000
max	99.000000	22.000000	4879.000000	12.000000	1.100000	1.375000	1.718750	1.718750	1000.000000	1.718750

```
#This command gives the order pair of new_cut_list dataset:

new_c.shape
```

```
(1000, 23)
```

```
#This command gives the column name of new_cut_list dataset:

new_c.columns
```

```
Index(['first_name', 'last_name', 'gender',
       'past_3_years_bike_related_purchases', 'DOB', 'job_title',
       'job_industry_category', 'wealth_segment', 'deceased_indicator',
       'owns_car', 'tenure', 'address', 'postcode', 'state', 'country',
       'property_valuation', 'Unnamed: 16', 'Unnamed: 17', 'Unnamed: 18',
       'Unnamed: 19', 'Unnamed: 20', 'Rank', 'Value'],
      dtype='object')
```

```
#This command shows the duplicate values of new_cut_list dataset:

new_c.duplicated().sum()
```

```
0
```

```
#This command shows the missing values of new_cut_list dataset:

new_c.isnull().sum()
```

```
first_name                             0
last_name                             29
gender                                 0
past_3_years_bike_related_purchases    0
DOB                                   17
job_title                            106
job_industry_category                165
wealth_segment                         0
deceased_indicator                     0
```

```
owns_car                            0
tenure                              0
address                             0
postcode                            0
state                               0
country                             0
property_valuation                  0
Unnamed: 16                         0
Unnamed: 17                         0
Unnamed: 18                         0
Unnamed: 19                         0
Unnamed: 20                         0
Rank                                0
Value                               0
dtype: int64
```

```
#This command drops some column:

new_c.drop(['Unnamed: 16', 'Unnamed: 17', 'Unnamed: 18', 'Unnamed: 19', 'Unnamed: 20'], axis=1, inplace=True)
```

```
#This command gives the order pair of new_cut_list dataset after dropping columns:

new_c.shape
```

```
(1000, 18)
```

```
#This command drops the missing rows:

new_c.dropna(inplace = True)
new_c.isnull().sum()
```

```
first_name                          0
last_name                           0
gender                              0
past_3_years_bike_related_purchases 0
DOB                                 0
job_title                           0
job_industry_category               0
wealth_segment                      0
deceased_indicator                  0
owns_car                            0
tenure                              0
address                             0
postcode                            0
state                               0
country                             0
property_valuation                  0
Rank                                0
Value                               0
dtype: int64
```

```
#This command gives the order pair of new_cut_list dataset after dropping missing rows:

new_c.shape
```

```
(715, 18)
```

```
#This command creates agre column based on DOB column:

new_c['DOB'] = pd.to_datetime(new_c['DOB'])
new_c['age'] = (dt.datetime.now() - new_c['DOB']) / np.timedelta64(1, 'Y')
```

```
#This command shows the maximum and minimum values in age column:

print("max age is: ",new_c.age.max())
print("min age is: ",new_c.age.min())
```

```
max age is:  85.4956364893638
min age is:  21.883105088992814
```

```
#This command create age_group column based on age column in new_customer_list dataset:

ag = pd.Series(['20-34','35-49', '50-64', '65-79', '80-94'], dtype='category')
new_c['age_group'] = ag

new_c.loc[new_c['age']<=34, 'age_group'] = ag[0]
new_c.loc[(new_c['age']>34) & (new_c['age']<=49), 'age_group'] = ag[1]
new_c.loc[(new_c['age']>49) & (new_c['age']<=64), 'age_group'] = ag[2]
new_c.loc[(new_c['age']>64) & (new_c['age']<=79), 'age_group'] = ag[3]
new_c.loc[new_c['age']>79, 'age_group'] = ag[4]
```

```
#This command shows the information of dataset and as well as it's first 5 rows:

print(new_c.info())
new_c.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 715 entries, 0 to 999
Data columns (total 20 columns):
 #   Column                               Non-Null Count  Dtype
---  ------                               --------------  -----
 0   first_name                           715 non-null    object
 1   last_name                            715 non-null    object
 2   gender                               715 non-null    object
 3   past_3_years_bike_related_purchases  715 non-null    int64
 4   DOB                                  715 non-null    datetime64[ns]
 5   job_title                            715 non-null    object
 6   job_industry_category                715 non-null    object
 7   wealth_segment                       715 non-null    object
 8   deceased_indicator                   715 non-null    object
 9   owns_car                             715 non-null    object
 10  tenure                               715 non-null    int64
 11  address                              715 non-null    object
 12  postcode                             715 non-null    int64
 13  state                                715 non-null    object
 14  country                              715 non-null    object
 15  property_valuation                   715 non-null    float64
```

```
#This command save the new_customer_list dataset:

new_c.to_csv('NewCustomer_list.csv', index=False)
```

```
dtypes: category(1), datetime64[ns](1), float64(3), int64(4), object(11)
```

Data Insight Analysis

```
#Load the dataset which we created and save in the variable called df:

df = pd.read_csv("/content/dataset.csv")
df
```

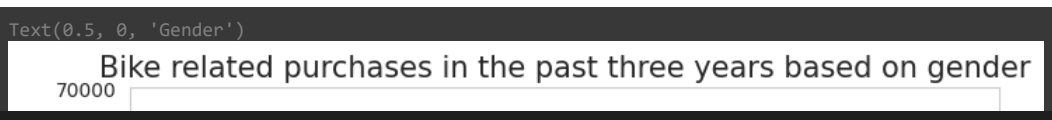
	customer_id	recency	frequency	profit	r	f	m	rfm_score	customer_profile	address	...	property_valuation	gender	past_3_years_bike_related_purchases	DOB
0	1	7.0	11	3018.09	4	4	3	443	Platinum	060 Morning Avenue	...	10	Female	93	1953-10-12
1	2	128.0	3	2226.26	1	1	2	112	Bronze	6 Meadow Vale Court	...	10	Male	81	1980-12-16
2	9	78.0	6	2353.11	2	3	2	232	Silver	97736 7th Trail	...	12	Female	97	1973-03-10
3	12	67.0	7	3540.03	2	3	3	233	Silver	44339 Golden Leaf Alley	...	4	Male	58	1994-07-21
4	13	27.0	7	4337.38	3	3	4	334	Gold	2 Sutherland Street	...	6	Male	38	1955-02-15
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2320	3493	93.0	6	3728.88	1	3	3	133	Bronze	3 Monument Crossing	...	10	Male	30	1964-02-29
2321	3494	4.0	4	2755.11	4	1	2	412	Platinum	35 Chive Alley	...	10	Male	72	1998-12-24
2322	3495	13.0	7	3847.65	4	3	3	433	Platinum	1 Dayton Park	...	9	Female	57	1987-07-12
2323	3496	256.0	4	2045.84	1	1	2	112	Bronze	2565 Caliangt Point	...	9	Male	99	1986-04-25
2324	3497	52.0	3	1648.32	2	1	1	211	Bronze	96 Delladonna Trail	...	5	Female	73	1986-05-03

2325 rows × 23 columns

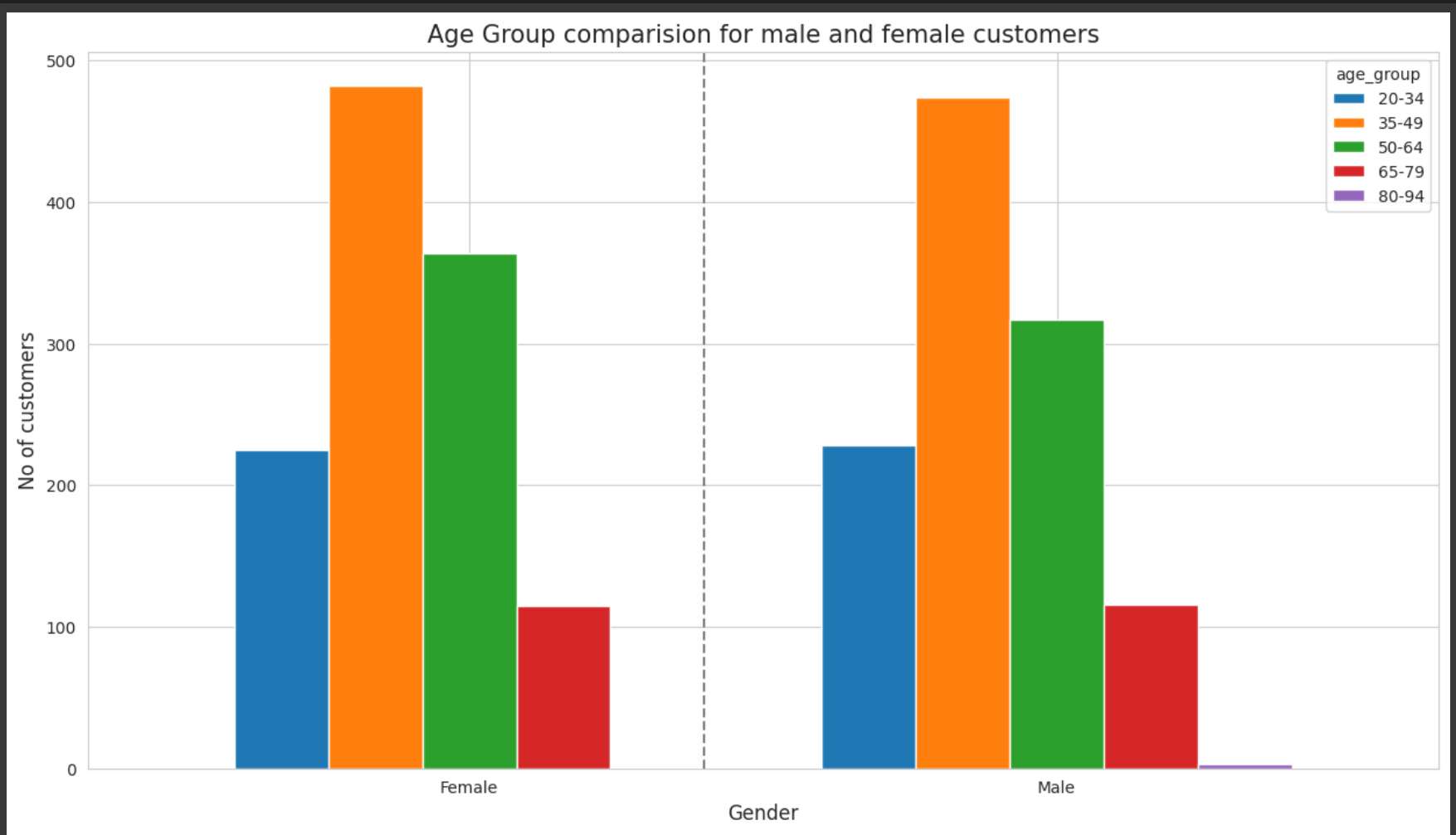
```
# Set grid for all figures
sns.set_style('whitegrid')

plt.rcParams['figure.figsize'] = (8,6)
```

```
#This command shows the graphical view of gender column based on past_3_years_bike_related_purchases column:

df1 = df.groupby('gender')['past_3_years_bike_related_purchases'].sum()
df1.plot(kind='bar')
plt.grid(axis='x')
plt.title('Bike related purchases in the past three years based on gender', fontsize=15)
plt.ylabel('Number of bike related purchases', fontsize=12)
plt.yticks(np.arange(0, 75000, 5000))
plt.xlabel('Gender', fontsize=12)
```

```
Text(0.5, 0, 'Gender')
```




```
#This command create a count plot of gender column based on age_group column:

counts = df.groupby(['gender', 'age_group']).size().reset_index(name='Count')
pivot_counts = counts.pivot(index='gender', columns='age_group', values='Count')
# Create a bar plot
pivot_counts.plot(kind='bar', figsize=(15, 8), width=0.8)
# Creating a line
plt.axvline(x=4 - 3.6, color='grey', linestyle='--')
plt.xlabel('Gender', fontsize=12)
plt.ylabel('No of customers', fontsize=12)
plt.title('Age Group comparision for male and female customers', fontsize=15)
plt.xticks(rotation = 0)
plt.show()
```

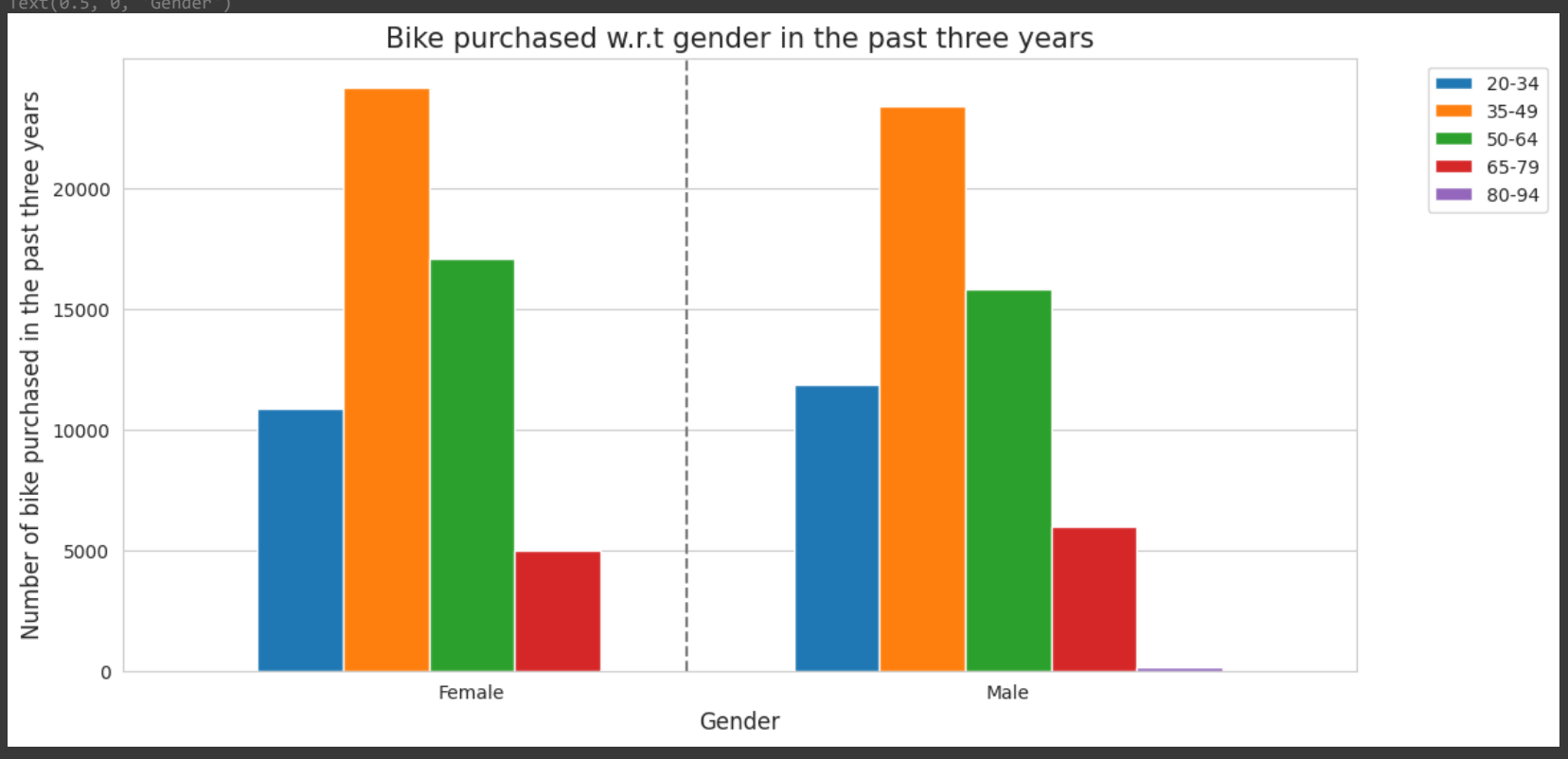



```
#This command shows the graphical view of customer_profile column based on gender column:

df2 = df.groupby(['customer_profile', 'gender']).size().unstack()
sort_cp = ['Platinum', 'Gold', 'Silver', 'Bronze']
df2 = df2.loc[sort_cp]

df2.apply(lambda x : x/x.sum(), axis=1).plot(kind='barh', stacked=True)
plt.axvline(x=1 - 0.5, color='grey', linestyle='--')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid(axis='y')
plt.title('Gender ratio in customer profile', fontsize=15)
plt.ylabel('Customer profile', fontsize=12)
plt.xlabel('Gender ratio', fontsize=12)
plt.xticks(np.arange(0, 1+0.1, 0.1))
```

```
([<matplotlib.axis.XTick at 0x786284eb8580>,
  <matplotlib.axis.XTick at 0x786284eb8550>,
  <matplotlib.axis.XTick at 0x786284e07040>,
  <matplotlib.axis.XTick at 0x786284d0aa40>,
  <matplotlib.axis.XTick at 0x786284d0ae30>,
  <matplotlib.axis.XTick at 0x786284d0b8e0>,
  <matplotlib.axis.XTick at 0x786284d283d0>,
```

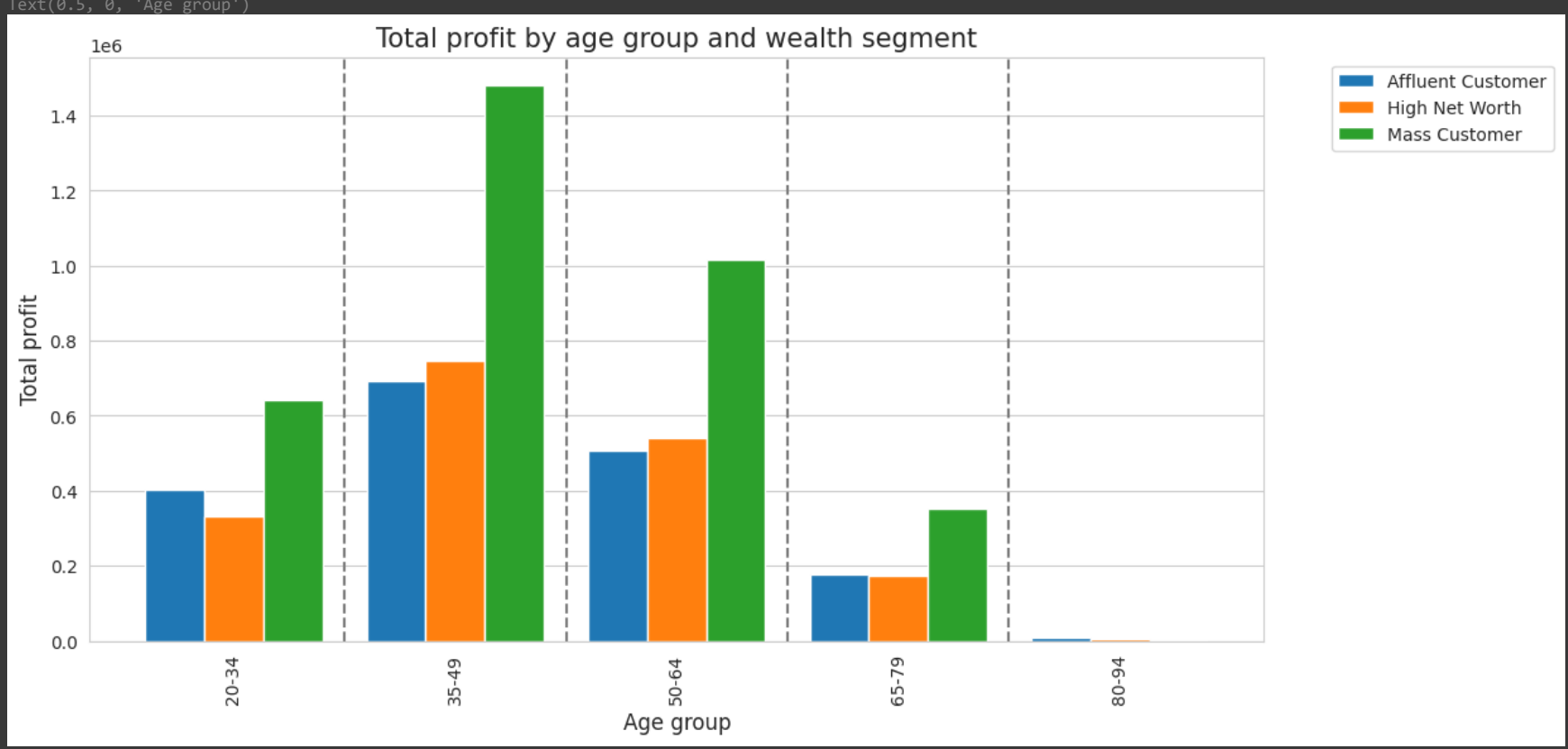
```
#This command shows the graphical view of gender column by it's age_group column based on past_3_years_bike_related_purchases column:

df1 = df.groupby(['gender', 'age_group'])['past_3_years_bike_related_purchases'].sum().unstack().fillna(0)
df1.plot(kind='bar', figsize=(12, 6), width=0.8)
plt.grid(axis='x')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.axvline(x=4 - 3.6, color='grey', linestyle='--')
plt.title('Bike purchased w.r.t gender in the past three years', fontsize=15)
plt.ylabel('Number of bike purchased in the past three years', fontsize=12)
plt.yticks(np.arange(0, 25000, 5000))
plt.xticks(rotation = 0)
plt.xlabel('Gender', fontsize=12)
```

```
Text(0.5, 0, 'Gender')
```



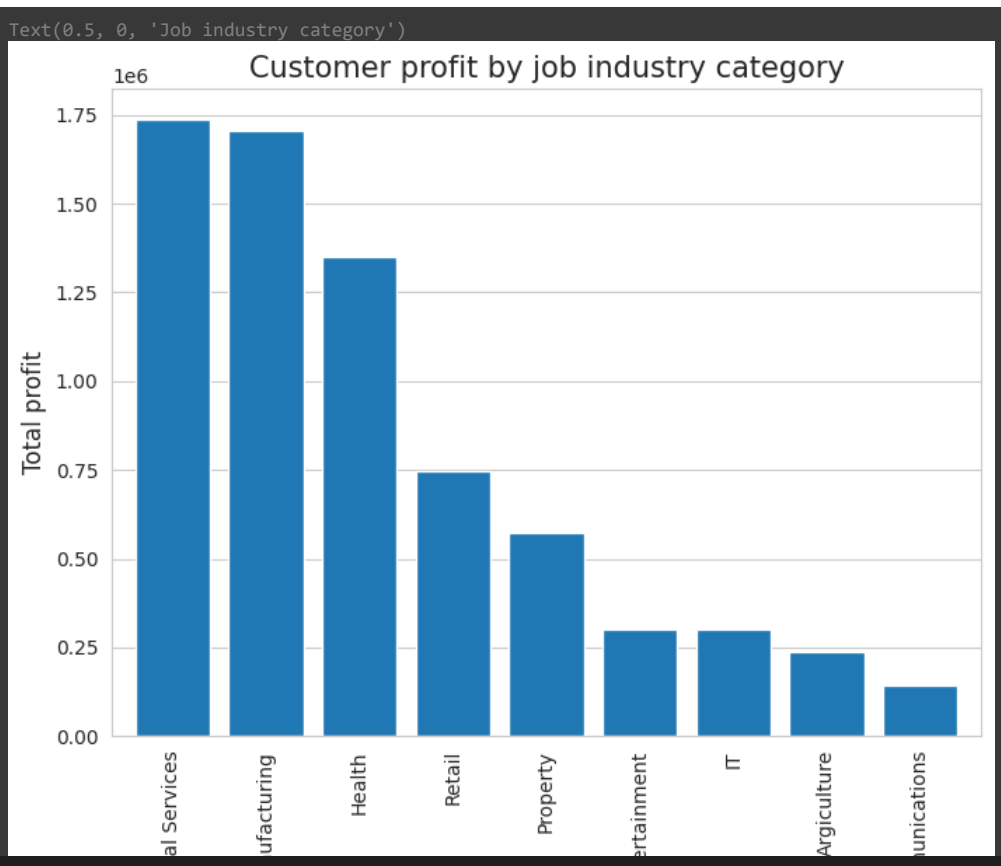

```
#This command shows the graphical view of age_group column by wealth_segment column based on profit:

df3 = df.groupby(['age_group', 'wealth_segment'])['profit'].sum().unstack().fillna(0)
df3.plot(kind='bar', figsize=(12, 6), width=0.8)
plt.grid(axis = 'x')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
# Creating a line
separation_lines = [1, 2, 3, 4]
for line in separation_lines:
    plt.axvline(x=line - 0.5, color='grey', linestyle='--')
plt.title('Total profit by age group and wealth segment', fontsize=15)
plt.ylabel('Total profit', fontsize=12)
plt.xlabel('Age group', fontsize=12)
```

```
Text(0.5, 0, 'Age group')
```



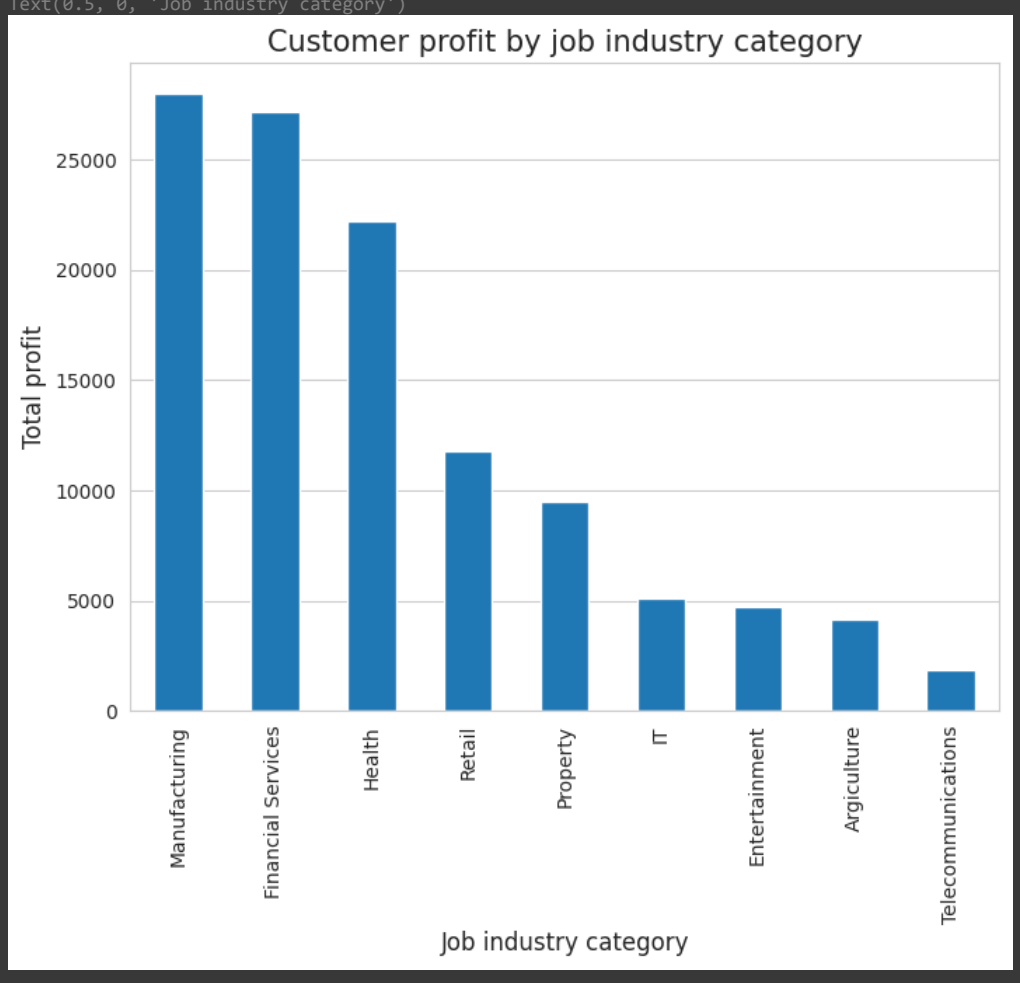

```
#This command plots the job_industry_category column based on profit:

df4 = df.groupby('job_industry_category')['profit'].sum()
df4 = df4.sort_values(ascending=False)

df4.plot(kind='bar', width=0.8)

plt.grid(axis='x')
plt.title('Customer profit by job industry category', fontsize=15)
plt.ylabel('Total profit', fontsize=12)
plt.xlabel('Job industry category', fontsize=12)
```

```
Text(0.5, 0, 'Job industry category')
```



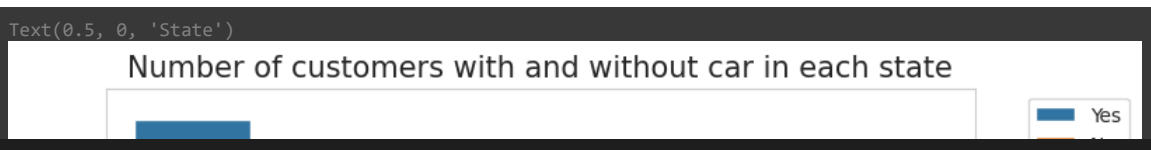

```
#This command plots the job_industry_category column based on past_3_years_bike_related_purchases:

df5 = df.groupby('job_industry_category')['past_3_years_bike_related_purchases'].sum()
df5 = df5.sort_values(ascending=False)

df5.plot(kind='bar')
plt.grid(axis='x')
plt.title('Customer profit by job industry category', fontsize=15)
plt.ylabel('Total profit', fontsize=12)
plt.xlabel('Job industry category', fontsize=12)
```

```
Text(0.5, 0, 'Job industry category')
```




```
#This command shows the graphical views of state column based on owns_car column:

sns.countplot(x='state', hue='owns_car', data=df)
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.title('Number of customers with and without car in each state', fontsize=15)
plt.ylabel('Number of customers', fontsize=12)
plt.xlabel('State', fontsize=12)
```

```
Text(0.5, 0, 'State')
```




```
#Load the New_customer_list dataset and save in the variable called reco:

reco = pd.read_csv("/content/NewCustomer_list.csv")
reco.head()
```

	first_name	last_name	gender	past_3_years_bike_related_purchases	DOB	job_title	job_industry_category	wealth_segment	deceased_indicator	owns_car	tenure	addr
0	Chickie	Brister	Male	86	1957-07-12	General Manager	Manufacturing	Mass Customer	N	Yes	14	Sho Ce
1	Morly	Genery	Male	69	1970-03-22	Structural Engineer	Property	Mass Customer	N	No	16	Mccorr F
2	Ardelis	Forrester	Female	10	1974-08-28	Senior Cost Accountant	Financial Services	Affluent Customer	N	No	10	Color Cros
3	Lucine	Stutt	Female	64	1979-01-28	Account Representative III	Manufacturing	Affluent Customer	N	Yes	5	Annan Pl
4	Melinda	Hadlee	Female	34	1965-09-21	Financial Analyst	Financial Services	Affluent Customer	N	No	19	Mont Pl

```
#The couple of line of code gives the high valuable customer in new_1000customer_list:

reco = reco[(reco['age_group']=='35-49') & (reco['wealth_segment']=='Mass Customer') &
                (reco['gender']=='Female') & (reco['owns_car']=='Yes') &
                 (reco['job_industry_category'].isin(['Manufacturing','Financial Services','Health'])) &
                 ( (reco['state']=='NSW') | (reco['state']=='VIC') ) ]

reco = reco.loc[:, ['first_name', 'last_name', 'gender', 'DOB', 'job_industry_category', 'wealth_segment', 'owns_car', 'state']]

print('It is recommended to target {} customers to bring maximum value to the organization.\n'.format(reco.shape[0]))

print('High potential value customers are as follows:')
pd.set_option('display.max_rows', None)
reco
```

```
It is recommended to target 12 customers to bring maximum value to the organization.

High potential value customers are as follows:
```

	first_name	last_name	gender	DOB	job_industry_category	wealth_segment	owns_car	state
25	Sybilla	MacCart	Female	1987-01-15	Financial Services	Mass Customer	Yes	NSW
31	Gale	Disbrow	Female	1977-05-14	Financial Services	Mass Customer	Yes	VIC
93	Daryl	Pauncefort	Female	1979-06-18	Financial Services	Mass Customer	Yes	NSW
197	Raye	Roo	Female	1976-03-07	Financial Services	Mass Customer	Yes	VIC
209	Biddie	Gorce	Female	1988-01-30	Financial Services	Mass Customer	Yes	NSW
340	Alexina	Mabley	Female	1975-10-12	Manufacturing	Mass Customer	Yes	NSW
348	Katleen	Arnoult	Female	1976-11-24	Manufacturing	Mass Customer	Yes	NSW
422	Ajay	Worham	Female	1979-09-30	Manufacturing	Mass Customer	Yes	NSW
438	Leisha	McConway	Female	1975-10-31	Financial Services	Mass Customer	Yes	VIC
478	Selle	Casper	Female	1978-03-27	Health	Mass Customer	Yes	NSW
499	Bertine	Smalles	Female	1983-12-10	Financial Services	Mass Customer	Yes	VIC
686	Jammie	Seldner	Female	1975-02-25	Health	Mass Customer	Yes	NSW