Flipkart Mobile Customer Analysis

Import necessary Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

Load the dataset

In [2]:
```
df=pd.read_csv('Flipkart Mobile 2.csv')
df
```

Out[2]:

	brand	model	base_color	processor	screen_size	ROM	RAM	display_size	num_rear_camera	num_front_c
0	Apple	iPhone SE	Black	Water	Very Small	64	2	4.7	1	
1	Apple	iPhone 12 Mini	Red	Ceramic	Small	64	4	5.4	2	
2	Apple	iPhone SE	Red	Water	Very Small	64	2	4.7	1	
3	Apple	iPhone XR	Others	iOS	Medium	64	3	6.1	1	
4	Apple	iPhone 12	Red	Ceramic	Medium	128	4	6.1	2	
...	...	...	...	...	...	...	...	...	...	

425	Xiaomi	Redmi 6 Pro	Black	Qualcomm	Small	32	3	5.8	2	
426	Xiaomi	Redmi 6 Pro	Red	Qualcomm	Small	64	4	5.8	2	
427	Xiaomi	Mi 11 Lite	Others	Qualcomm	Large	128	6	6.5	3	
428	Xiaomi	Redmi 8A Dual	Blue	Qualcomm	Medium	32	3	6.2	2	
429	Xiaomi	Redmi 6 Pro	Blue	Qualcomm	Small	32	3	5.8	2	

430 rows × 16 columns

Know your Dataset

In [3]:
```
df.head(5)
```

Out[3]:

	brand	model	base_color	processor	screen_size	ROM	RAM	display_size	num_rear_camera	num_front_came
0	Apple	iPhone SE	Black	Water	Very Small	64	2	4.7	1	
1	Apple	iPhone 12 Mini	Red	Ceramic	Small	64	4	5.4	2	
2	Apple	iPhone SE	Red	Water	Very Small	64	2	4.7	1	
3	Apple	iPhone XR	Others	iOS	Medium	64	3	6.1	1	
4	Apple	iPhone 12	Red	Ceramic	Medium	128	4	6.1	2	

In [4]:
```
df.tail(5)
```

Out[4]:

	brand	model	base_color	processor	screen_size	ROM	RAM	display_size	num_rear_camera	num_front_ca
425	Xiaomi	Redmi 6 Pro	Black	Qualcomm	Small	32	3	5.8	2	
426	Xiaomi	Redmi 6 Pro	Red	Qualcomm	Small	64	4	5.8	2	
427	Xiaomi	Mi 11 Lite	Others	Qualcomm	Large	128	6	6.5	3	
428	Xiaomi	Redmi 8A Dual	Blue	Qualcomm	Medium	32	3	6.2	2	
429	Xiaomi	Redmi 6 Pro	Blue	Qualcomm	Small	32	3	5.8	2	

In [5]:
```
df.shape
```

Out[5]:
```
(430, 16)
```

In [6]:
```
df.size
```
Out[6]:
```
6880
```

In [7]:
```
df.info()
```
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 430 entries, 0 to 429
Data columns (total 16 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   brand             430 non-null    object 
 1   model             430 non-null    object 
 2   base_color        430 non-null    object 
 3   processor         430 non-null    object 
 4   screen_size       430 non-null    object 
 5   ROM               430 non-null    int64  
 6   RAM               430 non-null    int64  
 7   display_size      430 non-null    float64
 8   num_rear_camera   430 non-null    int64  
 9   num_front_camera  430 non-null    int64  
 10  battery_capacity  430 non-null    int64  
 11  ratings           430 non-null    float64
 12  num_of_ratings    430 non-null    int64  
 13  sales_price       430 non-null    int64  
 14  discount_percent  430 non-null    float64
 15  sales             430 non-null    float64
dtypes: float64(4), int64(7), object(5)
memory usage: 53.9+ KB
```

In [8]:
```
df.describe()
```
Out[8]:

	ROM	RAM	display_size	num_rear_camera	num_front_camera	battery_capacity	ratings	nu
count	430.000000	430.000000	430.000000	430.000000	430.000000	430.000000	430.000000	
mean	105.748837	5.320930	6.369767	2.904651	1.044186	4529.397674	4.339302	
std	63.164064	2.182635	0.369549	0.952350	0.227280	986.907252	0.151494	
min	8.000000	1.000000	4.700000	1.000000	1.000000	1800.000000	3.000000	
25%	64.000000	4.000000	6.300000	2.000000	1.000000	4000.000000	4.300000	
50%	128.000000	4.000000	6.500000	3.000000	1.000000	4500.000000	4.300000	
75%	128.000000	6.000000	6.500000	4.000000	1.000000	5000.000000	4.400000	
max	512.000000	12.000000	7.600000	4.000000	3.000000	7000.000000	4.600000	6

In [9]:
```
df["ROM"].mean()
```
Out[9]:
```
105.74883720930232
```

How many Mobile Brands are there ?

In [10]:
```
df["brand"].unique()
```
Out[10]:
```
array(['Apple', 'Poco', 'Realme', 'Samsung', 'Xiaomi'], dtype=object)
```

Get Separate them all one by one

Group By Brand

In [11]:
```
branddf = df.groupby("brand")
branddf.groups
```

Out[11]:
```
{'Apple': [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21,
22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43,
44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55], 'Poco': [56, 57, 58, 59, 60, 61, 62, 6
3, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 8
5, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103, 104, 105,
106, 107, 108, 109, 110, 111], 'Realme': [112, 113, 114, 115, 116, 117, 118, 119, 120, 1
21, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132, 133, 134, 135, 136, 137, 138,
139, 140, 141, 142, 143, 144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 155, 15
6, 157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169, 170, 171, 172, 173,
174, 175, 176, 177, 178, 179, 180, 181, 182, 183, 184, 185, 186, 187, 188, 189, 190, 19
1, 192, 193, 194, 195, 196, 197, 198, 199, 200, 201, 202, 203, 204, 205, 206, 207, 208,
209, 210, 211, ...], 'Samsung': [250, 251, 252, 253, 254, 255, 256, 257, 258, 259, 260,
261, 262, 263, 264, 265, 266, 267, 268, 269, 270, 271, 272, 273, 274, 275, 276, 277, 27
8, 279, 280, 281, 282, 283, 284, 285, 286, 287, 288, 289, 290, 291, 292, 293, 294, 295,
296, 297, 298, 299, 300, 301, 302, 303, 304, 305, 306, 307, 308, 309, 310, 311, 312, 31
3, 314, 315, 316, 317, 318, 319, 320, 321, 322, 323, 324, 325, 326, 327, 328, 329, 330,
331, 332, 333, 334, 335, 336, 337, 338, 339, 340, 341, 342, 343, 344, 345, 346, 347, 34
8, 349, ...], 'Xiaomi': [369, 370, 371, 372, 373, 374, 375, 376, 377, 378, 379, 380, 38
1, 382, 383, 384, 385, 386, 387, 388, 389, 390, 391, 392, 393, 394, 395, 396, 397, 398,
399, 400, 401, 402, 403, 404, 405, 406, 407, 408, 409, 410, 411, 412, 413, 414, 415, 41
6, 417, 418, 419, 420, 421, 422, 423, 424, 425, 426, 427, 428, 429]}
```

In [12]:
```
appledf = branddf.get_group("Apple")
appledf.head()
```

Out[12]:

	brand	model	base_color	processor	screen_size	ROM	RAM	display_size	num_rear_camera	num_front_came
0	Apple	iPhone SE	Black	Water	Very Small	64	2	4.7	1	
1	Apple	iPhone 12 Mini	Red	Ceramic	Small	64	4	5.4	2	
2	Apple	iPhone SE	Red	Water	Very Small	64	2	4.7	1	
3	Apple	iPhone XR	Others	iOS	Medium	64	3	6.1	1	
4	Apple	iPhone 12	Red	Ceramic	Medium	128	4	6.1	2	

In [13]:
```
pocodf = branddf.get_group("Poco")
pocodf.head()
```

Out[13]:

	brand	model	base_color	processor	screen_size	ROM	RAM	display_size	num_rear_camera	num_front_(
56	Poco	C3	Black	MediaTek	Large	64	4	6.5	3	
57	Poco	M3	Blue	Qualcomm	Large	64	4	6.5	3	
58	Poco	M2 Reloaded	Blue	MediaTek	Large	64	4	6.5	4	
59	Poco	C3	Blue	MediaTek	Large	32	3	6.5	3	
60	Poco	M3	Black	Qualcomm	Large	64	6	6.5	3	

In [14]:
```
realmedf = branddf.get_group("Realme")
```

```
realmedf.head()
```

Out[14]:

	brand	model	base_color	processor	screen_size	ROM	RAM	display_size	num_rear_camera	num_front_ca
112	Realme	C20	Blue	MediaTek	Large	32	2	6.5	1	
113	Realme	C20	Gray	MediaTek	Large	32	2	6.5	1	
114	Realme	C11 2021	Gray	Others	Large	32	2	6.5	1	
115	Realme	C11 2021	Blue	Others	Large	32	2	6.5	1	
116	Realme	C21Y	Black	Others	Large	64	4	6.5	3	

In [15]:
```
samsungdf = branddf.get_group("Samsung")
samsungdf.head()
```

Out[15]:

	brand	model	base_color	processor	screen_size	ROM	RAM	display_size	num_rear_camera	num_front_
250	Samsung	Galaxy F22	Black	MediaTek	Medium	64	4	6.4	4	
251	Samsung	Galaxy F22	Blue	MediaTek	Medium	64	4	6.4	4	
252	Samsung	Galaxy F22	Blue	MediaTek	Medium	128	6	6.4	4	
253	Samsung	Galaxy F22	Black	MediaTek	Medium	128	6	6.4	4	
254	Samsung	Galaxy F12	Blue	Exynos	Large	64	4	6.5	4	

In [16]:
```
xiaomidf = branddf.get_group("Xiaomi")
xiaomidf.head()
```

Out[16]:

	brand	model	base_color	processor	screen_size	ROM	RAM	display_size	num_rear_camera	num_front_ca
369	Xiaomi	Redmi 9A	Black	MediaTek	Large	32	3	6.5	1	
370	Xiaomi	Mi 11X	White	Qualcomm	Large	128	6	6.7	3	
371	Xiaomi	Redmi 8A Dual	White	Qualcomm	Medium	32	3	6.2	2	
372	Xiaomi	Mi A3	Blue	Qualcomm	Medium	64	4	6.1	3	
373	Xiaomi	Redmi 9	Blue	MediaTek	Large	128	4	6.5	2	

How much is count for each brand ?

In [17]:
```
x1 = df["brand"].value_counts()
x1
```

Out[17]:
```
brand
Realme     138
Samsung    119
Xiaomi      61
```

```
Apple       56
Poco        56
Name: count, dtype: int64
```

Find out how many models having each brand

In [18]:
```
appledf["model"].value_counts()
```

Out[18]:
```
model
iPhone XR         18
iPhone 12         17
iPhone 12 Mini    16
iPhone SE          3
iPhone 8           1
iPhone 7 Plus      1
Name: count, dtype: int64
```

In [19]:
```
pocodf["model"].value_counts()
```

Out[19]:
```
model
M3             9
M2 Pro         9
C3             6
X3 Pro         6
F3 GT          6
X3             6
M3 Pro 5G      5
M2             4
M2 Reloaded    2
F1             2
X2             1
Name: count, dtype: int64
```

In [20]:
```
realmedf['model'].value_counts()
```

Out[20]:
```
model
GT Master Edition    9
X3 SuperZoom         6
7 Pro                6
Narzo 30             6
3i                   6
5 Pro                6
8 5G                 6
8 Pro                6
X7 Max               6
8                    6
X7 5G                4
Narzo 30 Pro 5G      4
C25                  4
C11 2021             4
Narzo 20             4
C2                   4
7                    4
C15                  4
Narzo 30A            4
C21                  4
Narzo 30 5G          4
X3                   3
GT 5G                3
Narzo 10A            3
6                    3
Narzo 20A            2
C20                  2
C11                  2
X7 Pro 5G            2
Narzo 20 Pro         2
```

```
C12                     2
8s 5G                   2
C21Y                    2
Narzo 10                2
6i                      1
Name: count, dtype: int64
```

In [21]:
```
samsungdf['model'].value_counts()
```

Out[21]:
```
model
Galaxy A21s                  7
Galaxy F62                   6
Galaxy F12                   6
Galaxy F41                   6
Galaxy A03s                  6
Galaxy A20s                  5
Galaxy F02s                  5
Galaxy A51                   5
Galaxy A12                   5
Galaxy F22                   4
Galaxy M02                   4
Galaxy A52s 5G               4
Galaxy Z Flip3 5G            4
Galaxy A22 5G                4
Galaxy A52                   3
Galaxy S20 FE                3
Galaxy Z Fold3 5G            3
Galaxy Note 20               3
Galaxy A50s                  2
Galaxy Note 20 Ultra 5G      2
Galaxy M01                   2
Galaxy Grand 2               2
Galaxy J7 - 6                2
Galaxy A71                   2
Galaxy A72                   2
Galaxy M31                   2
Galaxy M32                   2
M02s                         2
Galaxy A31                   2
Galaxy M11                   1
Galaxy S21 Plus              1
Galaxy S21                   1
Galaxy Note10 Lite           1
Galaxy M30s                  1
Galaxy M42                   1
Galaxy A10                   1
Galaxy A80                   1
Galaxy A20                   1
Galaxy A22                   1
Galaxy J6                    1
Galaxy A7                    1
Galaxy Fold 2                1
Galaxy S10                   1
Name: count, dtype: int64
```

In [22]:
```
xiaomidf['model'].value_counts()
```

Out[22]:
```
model
Redmi 6 Pro           6
Mi 11 Lite            6
Redmi Note 7 Pro      6
Redmi Note 6 Pro      5
Redmi Note 9 Pro      4
Redmi 9               3
Mi A3                 3
Mi 10T                3
```

```
Redmi Y3             3
Mi 10i               2
Redmi 8A Dual        2
Redmi Note 5 Pro     2
Redmi Note 7         2
Mi 11X               2
Redmi K20            2
Mi 10                1
Redmi 6A             1
Mi A1                1
Mi 11X Pro 5G        1
Redmi 9A             1
Redmi Y2             1
Mi 10T Pro           1
Redmi Note 5         1
Redmi Note 4         1
Redmi 5              1
Name: count, dtype: int64
```

Find out uniques models for each brand

In [23]:
```
appledf["model"].unique()
```

Out[23]:
```
array(['iPhone SE', 'iPhone 12 Mini', 'iPhone XR', 'iPhone 12',
       'iPhone 8', 'iPhone 7 Plus'], dtype=object)
```

In [24]:
```
appledf["model"].nunique()
```

Out[24]:
```
6
```

In [25]:
```
pocodf["model"].unique()
```

Out[25]:
```
array(['C3', 'M3', 'M2 Reloaded', 'X3 Pro', 'M3 Pro 5G', 'M2 Pro',
       'F3 GT', 'X3', 'F1', 'M2', 'X2'], dtype=object)
```

In [26]:
```
pocodf["model"].nunique()
```

Out[26]:
```
11
```

In [27]:
```
realmedf["model"].unique()
```

Out[27]:
```
array(['C20', 'C11 2021', 'C21Y', 'Narzo 30 5G', 'C21', 'Narzo 30',
       '8s 5G', 'Narzo 30A', '8 5G', '8 Pro', 'C15', '8',
       'GT Master Edition', 'X7 5G', '7', 'Narzo 30 Pro 5G', 'C12', 'C11',
       'X7 Max', 'GT 5G', '5 Pro', '3i', 'Narzo 20 Pro', '7 Pro',
       'X3 SuperZoom', 'X7 Pro 5G', 'C2', 'X3', '6', '6i', 'C25',
       'Narzo 20', 'Narzo 10A', 'Narzo 20A', 'Narzo 10'], dtype=object)
```

In [28]:
```
realmedf["model"].nunique()
```

Out[28]:
```
35
```

In [29]:
```
samsungdf["model"].unique()
```

Out[29]:
```
array(['Galaxy F22', 'Galaxy F12', 'M02s', 'Galaxy M02', 'Galaxy A22',
       'Galaxy A52s 5G', 'Galaxy M32', 'Galaxy Z Flip3 5G',
       'Galaxy A22 5G', 'Galaxy A21s', 'Galaxy A03s', 'Galaxy M31',
       'Galaxy A51', 'Galaxy A72', 'Galaxy A12', 'Galaxy F62',
       'Galaxy A31', 'Galaxy A52', 'Galaxy F02s', 'Galaxy M11',
       'Galaxy F41', 'Galaxy A71', 'Galaxy Note 20', 'Galaxy Z Fold3 5G',
       'Galaxy M01', 'Galaxy A50s', 'Galaxy Note 20 Ultra 5G',
       'Galaxy S20 FE', 'Galaxy Grand 2', 'Galaxy Fold 2', 'Galaxy A7',
       'Galaxy J6', 'Galaxy J7 - 6', 'Galaxy A10', 'Galaxy A20',
       'Galaxy A80', 'Galaxy S21 Plus', 'Galaxy M42', 'Galaxy M30s',
```

```
       'Galaxy A20s', 'Galaxy Note10 Lite', 'Galaxy S21', 'Galaxy S10'],
      dtype=object)
```

In [30]:
```
samsungdf["model"].nunique()
```

Out[30]:
```
43
```

In [31]:
```
xiaomidf["model"].unique()
```

Out[31]:
```
array(['Redmi 9A', 'Mi 11X', 'Redmi 8A Dual', 'Mi A3', 'Redmi 9',
       'Mi 11 Lite', 'Redmi Note 7 Pro', 'Mi 10i', 'Redmi Note 6 Pro',
       'Redmi Note 9 Pro', 'Redmi Note 5 Pro', 'Redmi Note 7', 'Redmi Y3',
       'Redmi K20', 'Redmi Note 4', 'Redmi Note 5', 'Mi 10T',
       'Mi 10T Pro', 'Redmi Y2', 'Mi 10', 'Redmi 6 Pro', 'Mi 11X Pro 5G',
       'Mi A1', 'Redmi 6A', 'Redmi 5'], dtype=object)
```

In [32]:
```
xiaomidf["model"].nunique()
```

Out[32]:
```
25
```

Analysing the sales column

- In our dataset we having column **sales_price** which shows sale price of perticular model.
- and we have another column **sales** having values in crores so we can Convert sales values from crores to actual revenue generated

In [33]:
```
df['revenue']= (df['sales']* 10000000).round().astype(int)
df.head(5)
```

Out[33]:

	brand	model	base_color	processor	screen_size	ROM	RAM	display_size	num_rear_camera	num_front_came
0	Apple	iPhone SE	Black	Water	Very Small	64	2	4.7	1	
1	Apple	iPhone 12 Mini	Red	Ceramic	Small	64	4	5.4	2	
2	Apple	iPhone SE	Red	Water	Very Small	64	2	4.7	1	
3	Apple	iPhone XR	Others	iOS	Medium	64	3	6.1	1	
4	Apple	iPhone 12	Red	Ceramic	Medium	128	4	6.1	2	

- from this now we can calculate number of units sold for each model

In [34]:
```
#Divide revenue generated by sales price to get units sold

df['units_sold']= (df['revenue']/df['sales_price']).round().astype(int)
df.head(5)
```

Out[34]:

	brand	model	base_color	processor	screen_size	ROM	RAM	display_size	num_rear_camera	num_front_came
0	Apple	iPhone SE	Black	Water	Very Small	64	2	4.7	1	
1	Apple	iPhone	Red	Ceramic	Small	64	4	5.4	2	

		12 Mini							
2	Apple	iPhone SE	Red	Water	Very Small	64	2	4.7	1
3	Apple	iPhone XR	Others	iOS	Medium	64	3	6.1	1
4	Apple	iPhone 12	Red	Ceramic	Medium	128	4	6.1	2

In [35]:
```
df.units_sold.sum()
```
Out[35]:
```
7376835
```

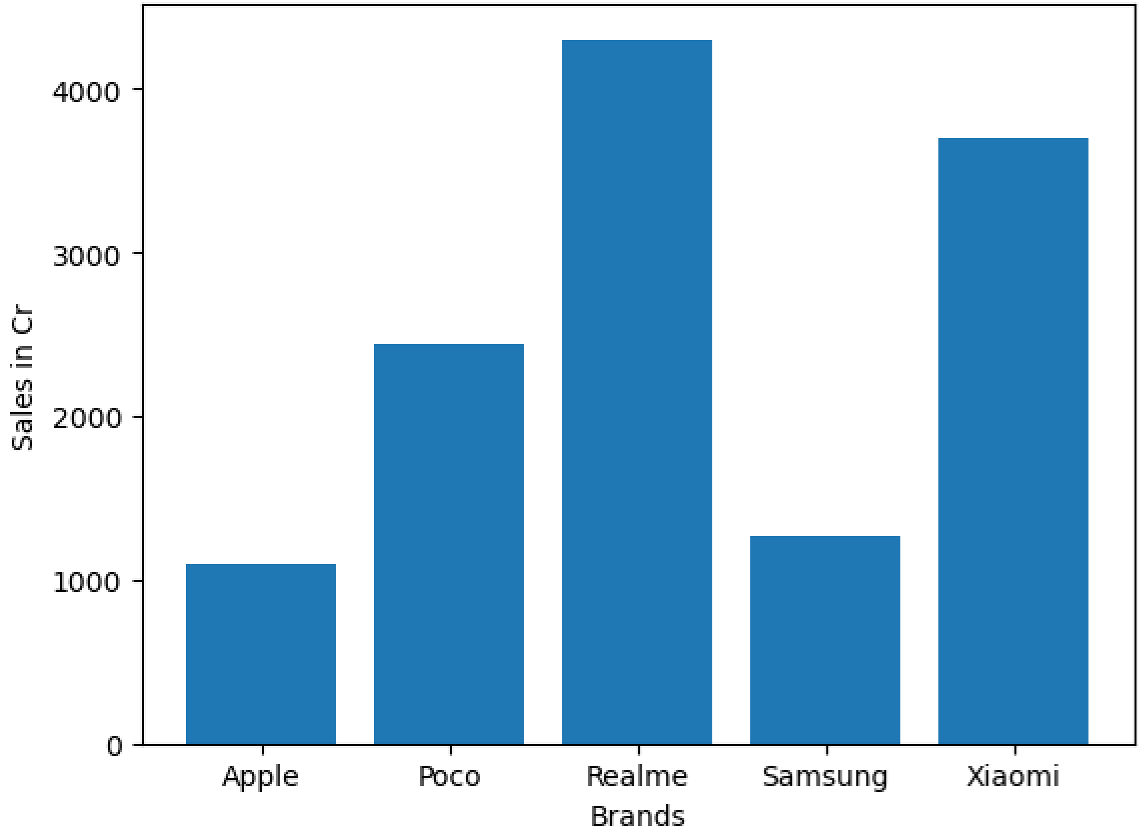
In [36]:
```
print('sales generated in crocres',df.sales.sum(),"cr")
```
```
sales generated in crocres 12793.5 cr
```

In [37]:
```
df.revenue.sum()/10000000
```
Out[37]:
```
9623.848176
```

1. Find out how many brands are there having most of the sales.

In [38]:
```
sales = branddf.sales.sum()
sales
```
Out[38]:
```
brand
Apple       1091.27
Poco        2437.32
Realme      4301.91
Samsung     1261.90
Xiaomi      3701.10
Name: sales, dtype: float64
```

In [69]:
```
plt.bar(sales.index,sales)
plt.xlabel('Brands')
plt.ylabel('Sales in Cr')
plt.show()
```



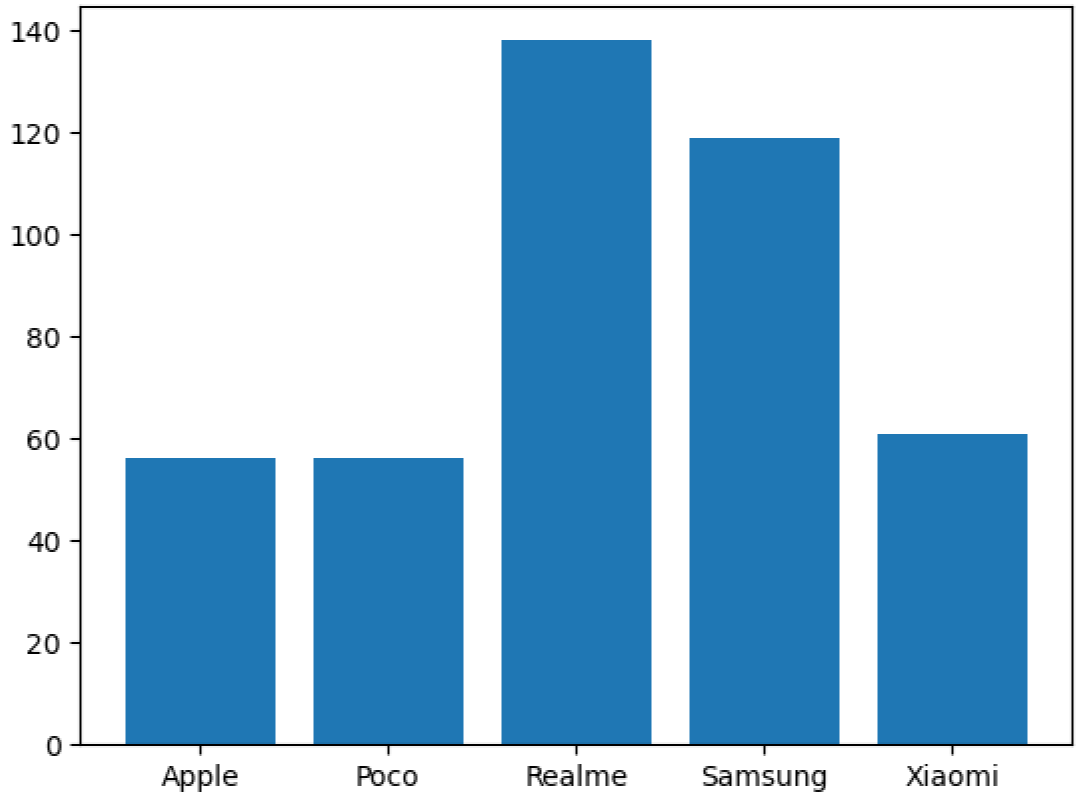
- **Realme is Dominated** From this we can say that **Realme** generate more sales

2. How many models are sold by each brand?

In [40]:
```
sold_models = branddf.model.count()
sold_models
```

Out[40]:
```
brand
Apple       56
Poco        56
Realme     138
Samsung    119
Xiaomi      61
Name: model, dtype: int64
```

In [70]:
```
plt.bar(sold_models.index,sold_models)
plt.show()
```

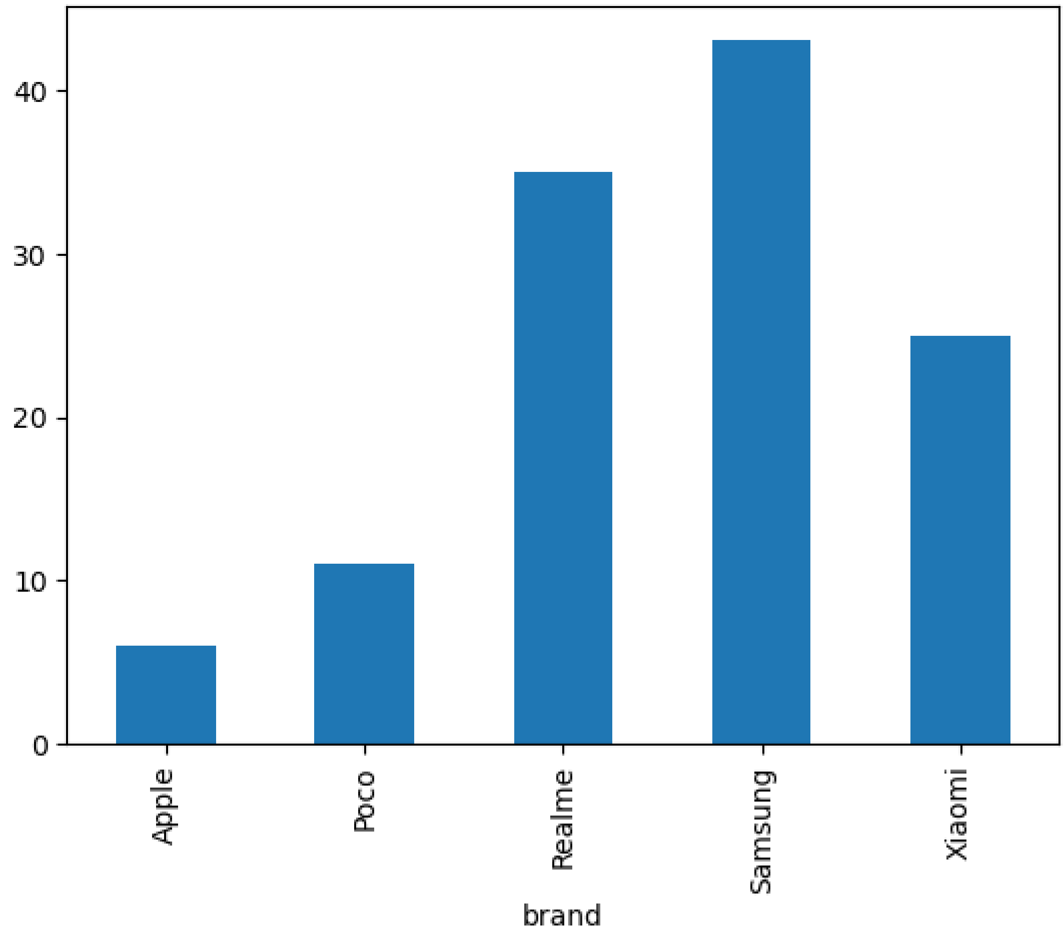


we can also find out how many unique models sold by each brand

In [42]:
```
unique_models=branddf.model.nunique()
unique_models
```

Out[42]:
```
brand
Apple       6
Poco       11
Realme     35
Samsung    43
Xiaomi     25
Name: model, dtype: int64
```

In [71]:
```
unique_models.plot(kind='bar')
plt.show()
```



- **Realme's Models are Dominance**: Realme's total sales volume across its models is higher compared to any other brand in the dataset. This indicates that Realme is very successful in selling its existing models.
- **Samsung's Model Diversity**: Even though Realme leads in total sales, Samsung offers a wider range of distinct smartphone models. This suggests that Samsung has a more diverse product portfolio, with a variety of models catering to different market segments or consumer preferences.

3. What is the average discount given by brands on their models?

To create the actual discount value from the "discount_percent" column, we can simply calculate it as a percentage of the sales price.

In [44]:
```
df['actual_discount']= df['sales_price']*df['discount_percent']
```

In [72]:
```
df.head()
```

Out[72]:

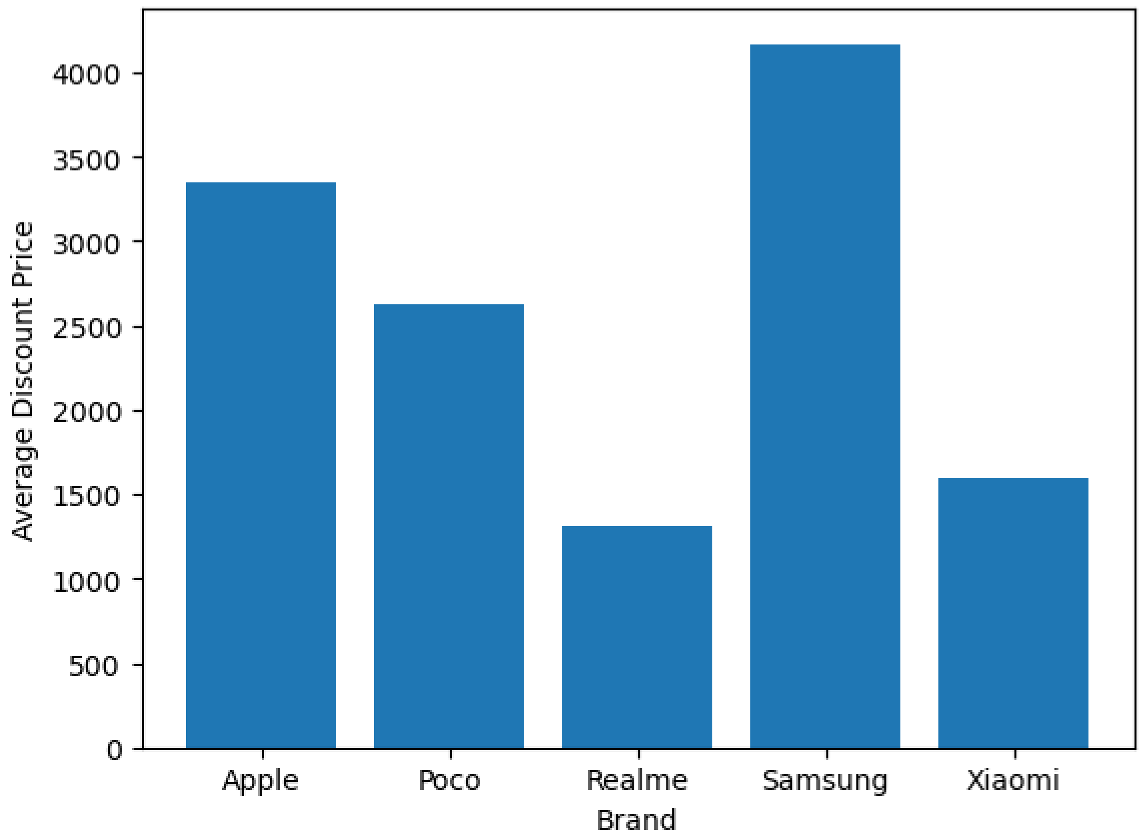
	brand	model	base_color	processor	screen_size	ROM	RAM	display_size	num_rear_camera	num_front_came
0	Apple	iPhone SE	Black	Water	Very Small	64	2	4.7	1	
1	Apple	iPhone 12 Mini	Red	Ceramic	Small	64	4	5.4	2	
2	Apple	iPhone SE	Red	Water	Very Small	64	2	4.7	1	
3	Apple	iPhone XR	Others	iOS	Medium	64	3	6.1	1	

4	Apple	iPhone 12	Red	Ceramic	Medium	128	4	6.1	2

In [46]:
```
avg_discount = df.groupby('brand').actual_discount.mean()
avg_discount
```

Out[46]:
```
brand
Apple      3353.346429
Poco       2625.016429
Realme     1315.306884
Samsung    4170.121092
Xiaomi     1600.749180
Name: actual_discount, dtype: float64
```

In [73]:
```
plt.bar(avg_discount.index,avg_discount)
plt.xlabel('Brand')
plt.ylabel('Average Discount Price')
plt.show()
```



- **Samsung's** higher average discount may reflect its positioning in the market.
- By offering more significant discounts, Samsung could be targeting a broader customer base, including price-sensitive consumers who are attracted to discounts and promotions.
- Offering higher average discounts can make Samsung's products more appealing to consumers,

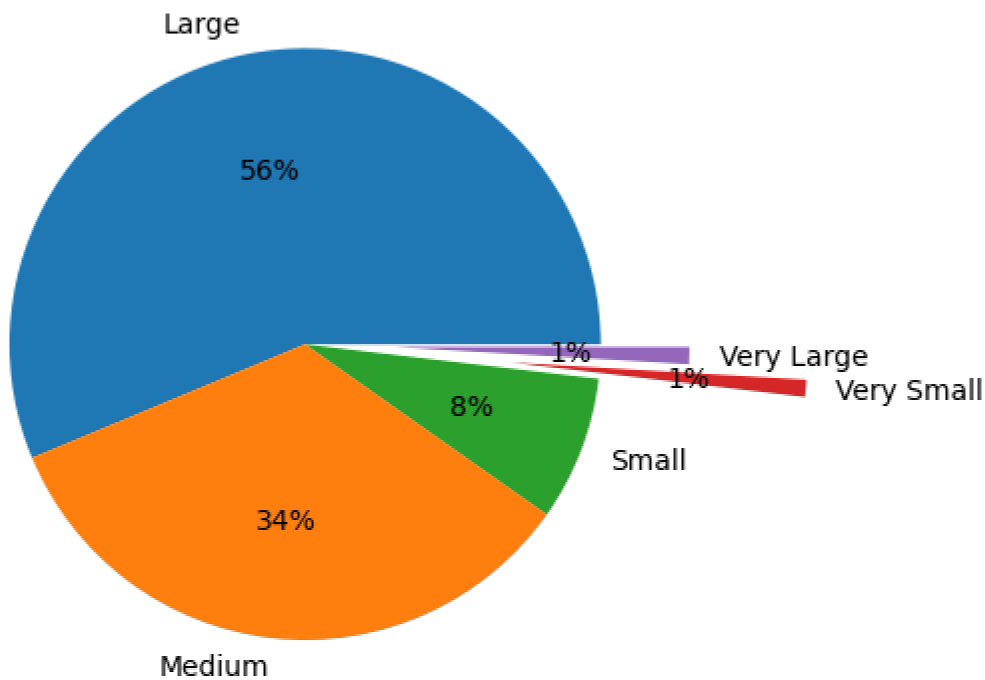
4. What size of display did customers like the most?

In [48]:
```
screen= df.screen_size.value_counts()
screen
```

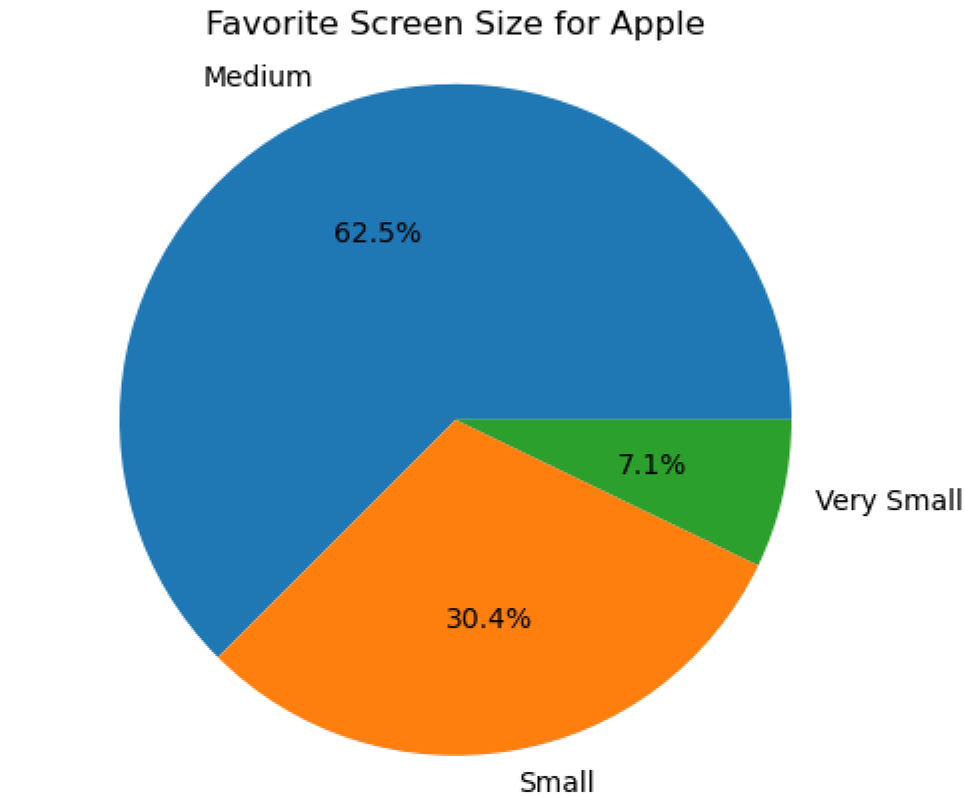
Out[48]:
```
screen_size
Large     242
Medium    146
Small      34
```

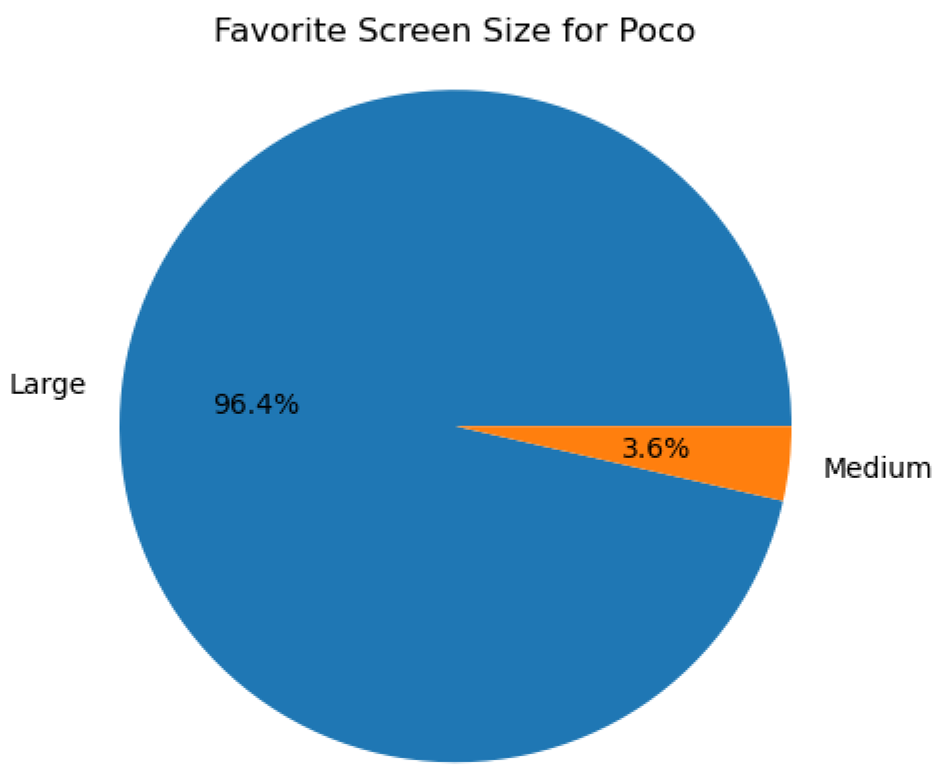
```
Very Small      4
Very Large      4
Name: count, dtype: int64
```

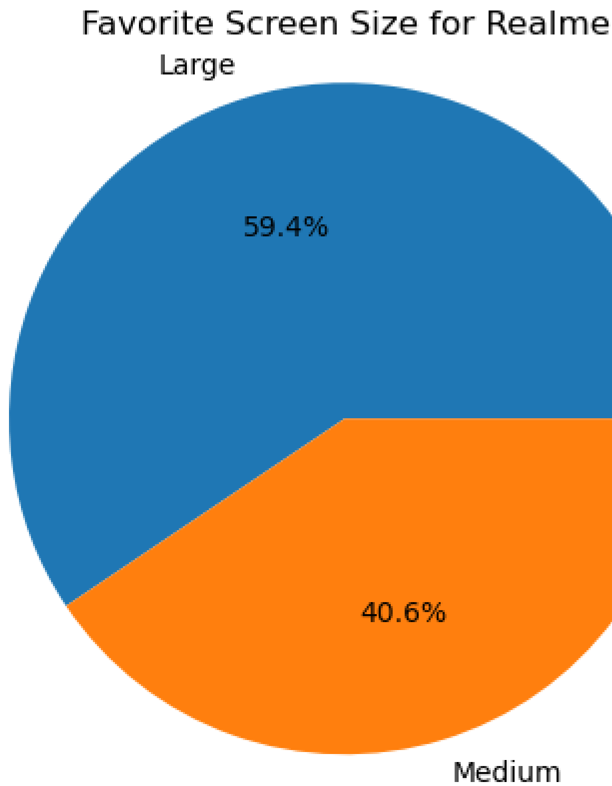
In [49]:
```
plt.pie(screen, labels=screen.index, autopct='%0.f%%',explode=[0,0,0,0.7,0.3])
plt.show()
```

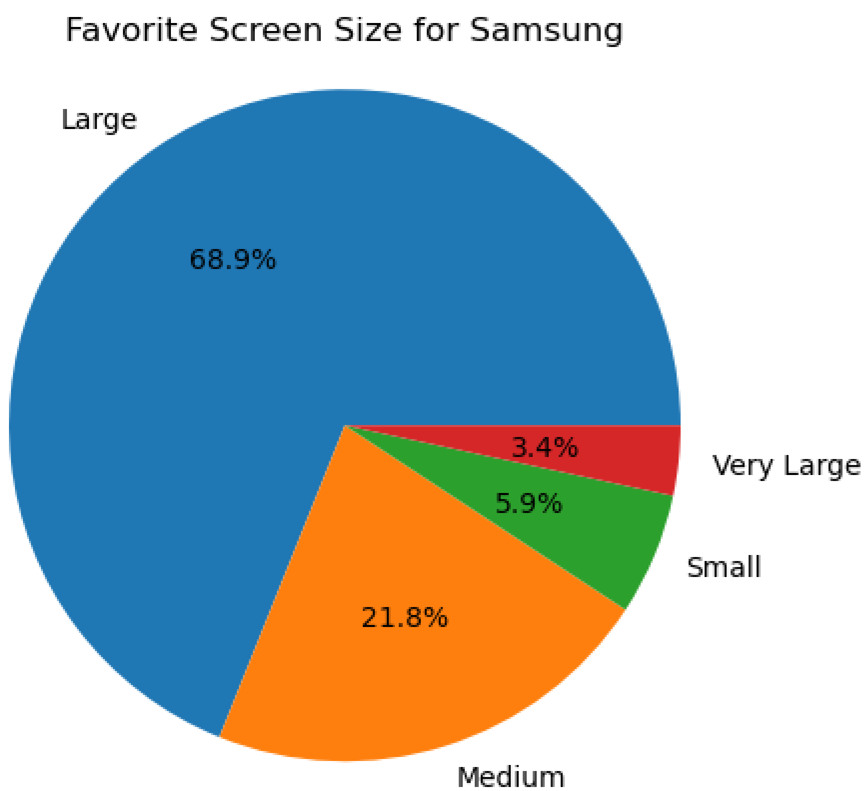


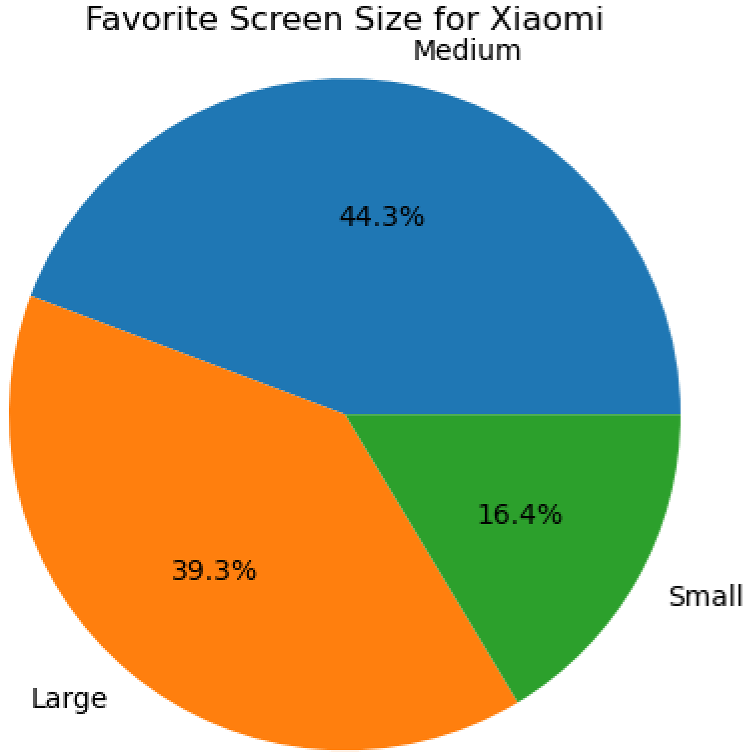
In [50]:
```
#'branddf' is grouped DataFrame containing data grouped by brand
# Iterate over each brand

for brand, brand_df in branddf:
    # Filter DataFrame for the current brand
    brand_screen_sizes = brand_df['screen_size']
    screen_size_counts = brand_screen_sizes.value_counts()     # Calculate the counts of

    # Plot pie chart for the current brand
    #plt.figure(figsize=(6, 6))
    plt.pie(screen_size_counts, labels=screen_size_counts.index, autopct='%1.1f%%', star
    plt.title(f'Favorite Screen Size for {brand}')
    plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle
    plt.show()
```


Favorite Screen Size for Apple
Medium
62.5%
7.1%
Very Small
30.4%
Small


Favorite Screen Size for Poco
Large
96.4%
3.6%
Medium


Favorite Screen Size for Realme
Large
59.4%
40.6%
Medium


Favorite Screen Size for Samsung
Large
68.9%
3.4%
Very Large
5.9%
Small
21.8%
Medium

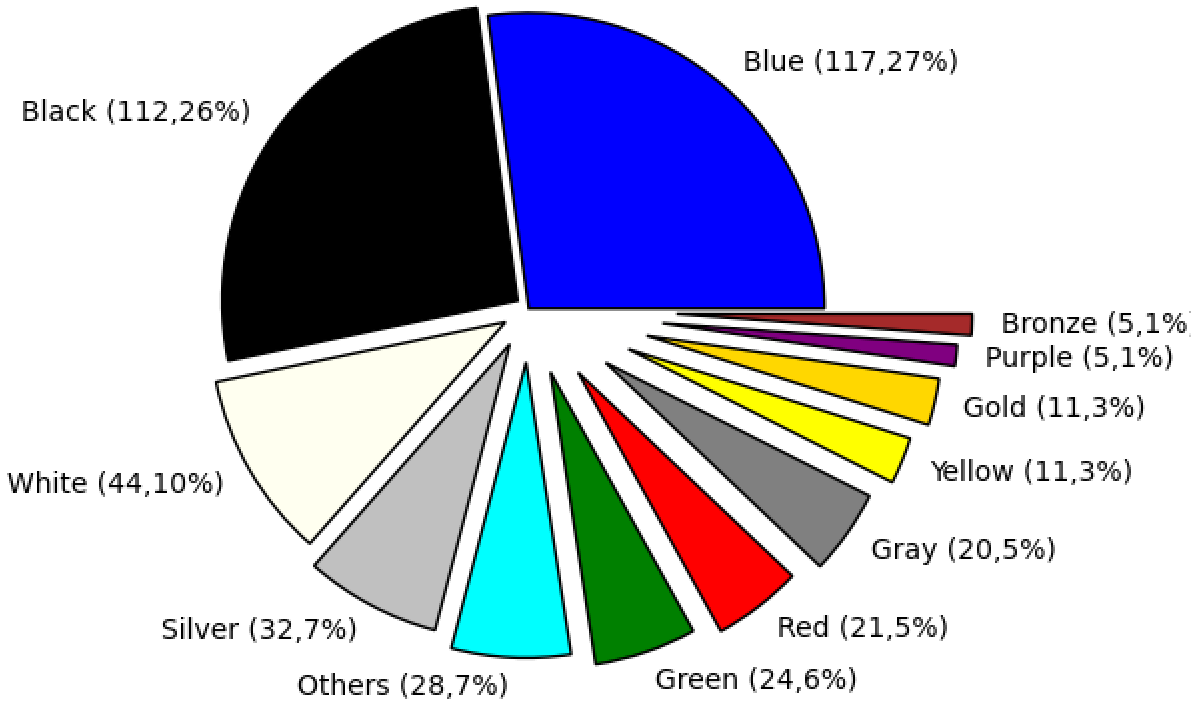


5. Which are the favorite colors of mobile phone customers?

In [52]:
```
color = df['base_color'].value_counts()
color
```

Out[52]:
```
base_color
Blue      117
Black     112
White      44
Silver     32
Others     28
Green      24
Red        21
Gray       20
Yellow     11
Gold       11
Purple      5
Bronze      5
Name: count, dtype: int64
```

In [74]:
```
autopct_color='orange'
combined_labels = [f"{label} ({size},{size/430*100:.0f}%)" for label, size in zip(color.
c1=['blue','black','ivory','silver','cyan','green','red','grey','yellow','gold','purple'
plt.pie(color,labels=combined_labels, colors=c1,explode=np.linspace(0,0.5,12) ,wedgeprop
plt.show()
```



In [54]:
```
branddf['base_color'].value_counts()
```

Out[54]:
```
brand    base_color
Apple    Black         12
         White         11
         Blue           8
         Red            7
         Green          6
         Others         4
         Purple         4
         Yellow         3
         Gold           1
Poco     Blue          18
         Black         17
         Yellow         5
         Others         3
         Red            3
         Silver         3
         Gray           3
         Bronze         2
         Green          2
Realme   Blue          43
         Black         26
         Silver        24
         White         16
         Gray           9
         Others         9
         Green          5
         Yellow         3
         Red            2
         Purple         1
Samsung  Black         38
         Blue          33
         Green         10
         White         10
         Others         9
         Gray           7
         Red            4
         Silver         3
```

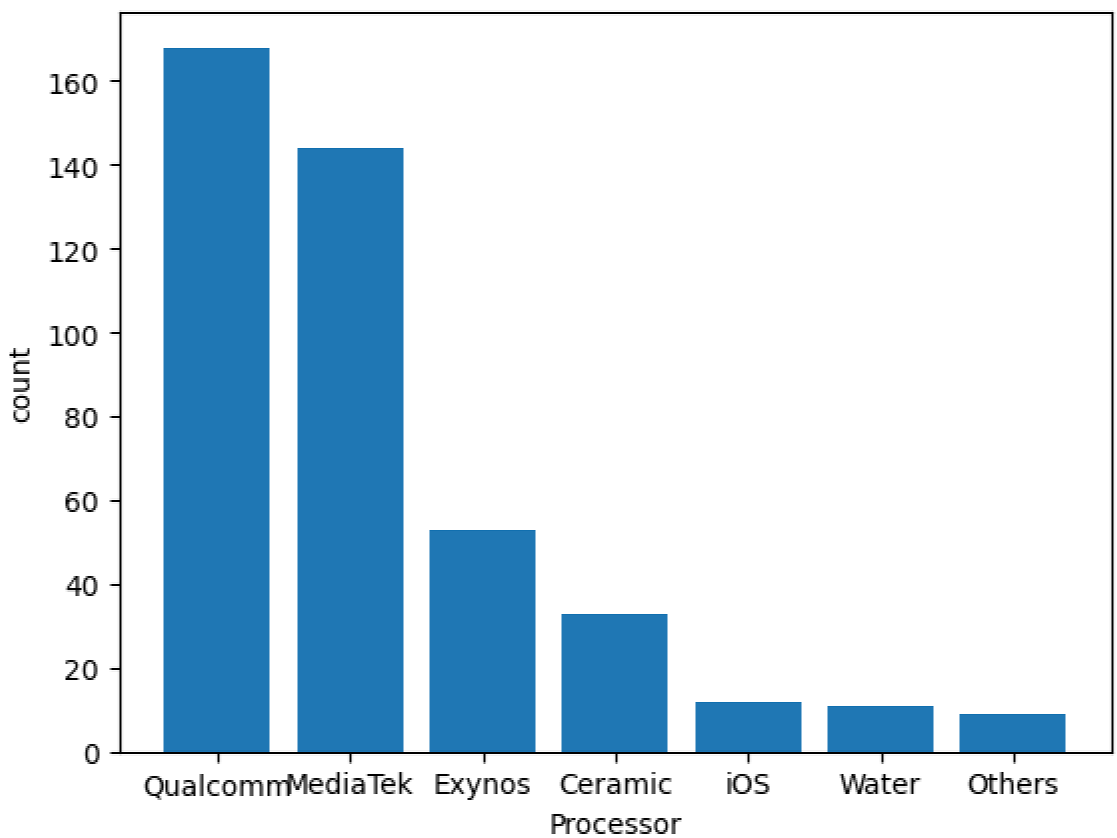
```
         Bronze          3
         Gold            2
Xiaomi   Black          19
         Blue           15
         Gold            8
         White           7
         Red             5
         Others          3
         Silver          2
         Gray            1
         Green           1
Name: count, dtype: int64
```

6. Which processors are the most favorable for customers?

In [55]:
```
pro = df['processor'].value_counts()
pro
```

Out[55]:
```
processor
Qualcomm    168
MediaTek    144
Exynos       53
Ceramic      33
iOS          12
Water        11
Others        9
Name: count, dtype: int64
```

In [56]:
```
plt.bar(pro.index,pro)
plt.xlabel('Processor')
plt.ylabel('count')
plt.show()
```



In [57]:
```
branddf.processor.value_counts()
```

Out[57]:
```
brand    processor
Apple    Ceramic        33
```

```
         iOS          12
         Water        11
Poco     Qualcomm     33
         MediaTek     23
Realme   MediaTek     91
         Qualcomm     41
         Others        6
Samsung  Exynos       53
         Qualcomm     38
         MediaTek     25
         Others        3
Xiaomi   Qualcomm     56
         MediaTek      5
Name: count, dtype: int64
```

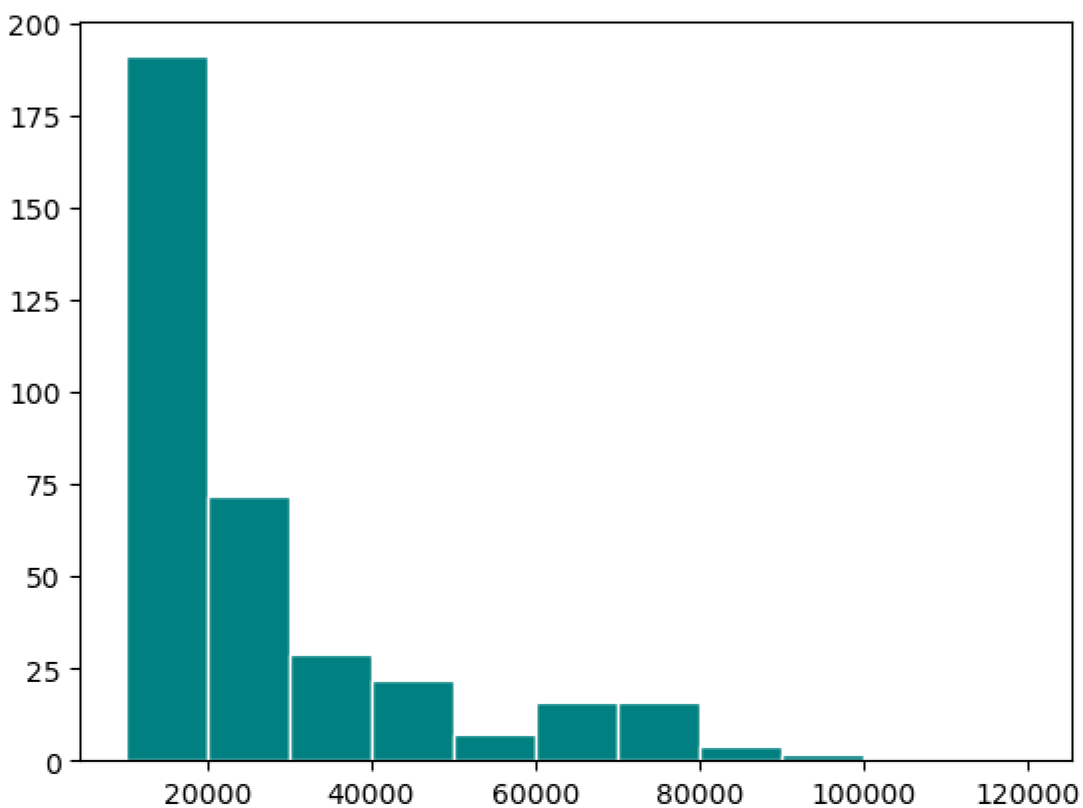
7. Find out mobile phones at various price ranges. which budget range do customers choose mostly?

In [77]:
```
df.columns
```

Out[77]:
```
Index(['brand', 'model', 'base_color', 'processor', 'screen_size', 'ROM',
       'RAM', 'display_size', 'num_rear_camera', 'num_front_camera',
       'battery_capacity', 'ratings', 'num_of_ratings', 'sales_price',
       'discount_percent', 'sales', 'revenue', 'units_sold',
       'actual_discount'],
      dtype='object')
```

In [59]:
```
plt.hist(df.sales_price, bins=[10000,20000,30000,40000,50000,60000,70000,80000,90000,100
```

Out[59]:
```
(array([191.,  72.,  29.,  22.,   7.,  16.,  16.,   4.,   2.,   0.]),
 array([ 10000.,  20000.,  30000.,  40000.,  50000.,  60000.,  70000.,
         80000.,  90000., 100000., 120000.]),
 <BarContainer object of 10 artists>)
```



Majority of customers buy mobile phones within a range of 10000 to 20000 which are **budget-friendly smartphones**

8. Which are the top 10 models by avg sales

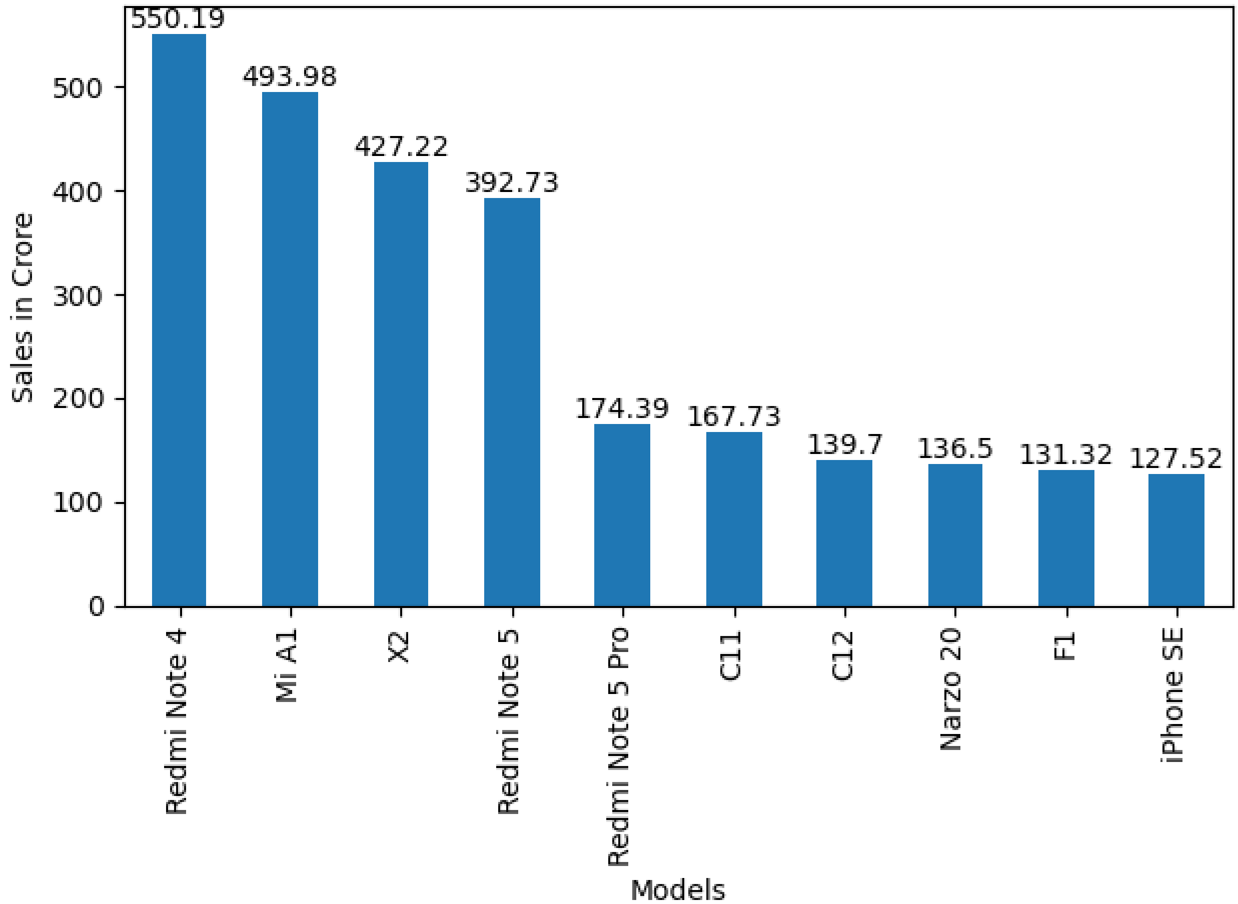
In [60]:
```
avg_sales_by_model = df.groupby('model')['sales'].mean()
avg_sales_by_model
```

Out[60]:
```
model
3i                   28.195000
5 Pro                27.838333
6                    72.176667
6i                   78.020000
7                    67.975000
                       ...
iPhone 12 Mini        1.569375
iPhone 7 Plus       109.940000
iPhone 8             43.990000
iPhone SE           127.520000
iPhone XR            24.415000
Name: sales, Length: 119, dtype: float64
```

In [61]:
```
top_10_models = avg_sales_by_model.sort_values(ascending=False).head(10)
top_10_models
```

Out[61]:
```
model
Redmi Note 4         550.190
Mi A1                493.980
X2                   427.220
Redmi Note 5         392.730
Redmi Note 5 Pro     174.395
C11                  167.730
C12                  139.700
Narzo 20             136.495
F1                   131.320
iPhone SE            127.520
Name: sales, dtype: float64
```

In [62]:
```
top_10_models.plot(kind = 'bar')
plt.xlabel('Models')
plt.ylabel('Sales in Crore')
for i, value in enumerate(top_10_models):
    plt.text(i, value, str(round(value, 2)), ha='center', va='bottom')

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



9. What is Battery capacity by brand

In [63]:
```
branddf.battery_capacity.value_counts()
```

Out[63]:
```
brand    battery_capacity
Apple    2815                  33
         2942                  18
         1800                   5
Poco     5000                  26
         6000                  15
         5160                   6
         5065                   6
         4000                   2
         4500                   1
Realme   5000                  53
         4500                  25
         6000                  18
         4300                  13
         4200                   9
         4230                   6
         4035                   6
         4310                   4
         4000                   4
Samsung  5000                  40
         6000                  21
         4500                  16
         4000                  16
         3300                   7
         7000                   6
         4300                   3
         4400                   3
         3400                   2
         2600                   2
         3000                   1
```

```
        4800                  1
        3700                  1
Xiaomi  4000                 27
        5000                 10
        4250                  6
        5020                  4
        4520                  3
        4030                  3
        4820                  2
        3080                  2
        3000                  1
        4100                  1
        4780                  1
        3300                  1
Name: count, dtype: int64
```

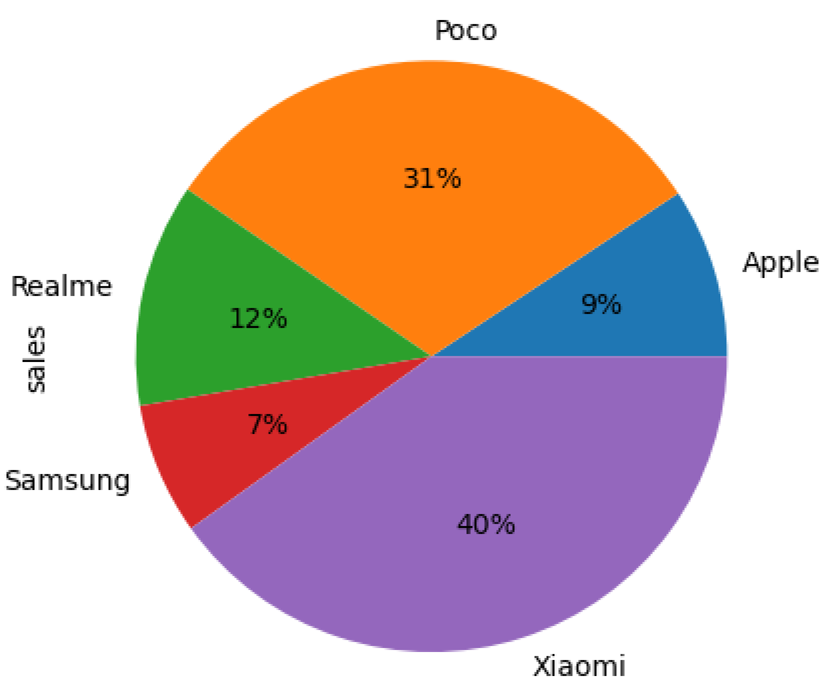
10. How much sales created by each brand ?

In [64]:
```
s = branddf.sales.max()
s
```

Out[64]:
```
brand
Apple      127.52
Poco       427.22
Realme     167.73
Samsung     98.89
Xiaomi     550.19
Name: sales, dtype: float64
```

In [65]:
```
s.plot(kind = "pie", autopct="%0.f%%")
```

Out[65]:
```
<Axes: ylabel='sales'>
```



Xiaomi generate **40%** of maximum sales as compared to other brands

Conclusion of Flipkart Mobile Analysis Project

Analyzing Flipkart's mobile phone sales data has provided valuable insights into customer preferences and behaviors. Here's a summary of the findings based on the problem statements provided:

Most Popular Brands:

The data shows a few brands dominate the sales, capturing the majority of the market share. These top brands have established strong customer loyalty and brand recognition.

Number of Models Sold by Each Brand:

Brands with a wide variety of models tend to attract more customers by catering to different preferences and price ranges. The top brands offer a diverse range of models, contributing to their high sales figures.

Average Discount Given by Brands:

Discount strategies vary across brands, but overall, offering competitive discounts is a common practice to boost sales. The average discount percentage can indicate how aggressively a brand is trying to attract price-sensitive customers.

Most Preferred Display Size:

Customers show a clear preference for certain display sizes, with mid-sized screens being the most popular. This indicates a balanced demand for portability and screen real estate.

Favorite Colors of Mobile Phone Customers:

Certain colors, such as black and blue, emerge as favorites among customers. These preferences can guide brands in deciding which color variants to prioritize in production and marketing.

Most Favorable Processors:

Processors from well-known manufacturers like Qualcomm and MediaTek are highly favored, reflecting customer preference for performance and reliability.

Price Range Preferences:

The analysis reveals that customers predominantly choose mobile phones within a specific budget range, highlighting the importance of affordability. Mid-range phones often strike the best balance between features and cost, making them the most popular.

Top 10 Models by Average Sales:

The top 10 models showcase a mix of features that are highly valued by customers, such as battery life, camera quality, and brand trust. These models serve as benchmarks for successful product offerings.

Battery Capacity by Brand:

Brands offering higher battery capacities tend to be more successful, as battery life remains a critical factor for many customers. This insight can help brands focus on enhancing battery performance in future models.

Sales Volume by Brand:

The sales volume analysis underscores the dominance of certain brands in the market. Brands with high sales volumes have effectively leveraged their brand reputation, product quality, and marketing strategies to capture significant market share.

Final Thoughts

The analysis of Flipkart's mobile phone sales data has provided actionable insights for understanding customer behavior. By recognizing the trends in brand preferences, display size, color choices, processor favorability, and price range preferences, brands can tailor their product offerings and marketing strategies to better meet customer needs. The findings highlight the importance of product variety, competitive pricing, and feature optimization in driving sales growth and customer satisfaction.

Thank You !