Importing Libraries

In [1]:

```
# General Libraries
import pandas as pd
import numpy as np

# Visualization Libraries
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib
import re, warnings
from datetime import datetime
from IPython.display import HTML

warnings.filterwarnings("ignore")
plt.rcParams['figure.figsize'] = [15, 10]
```

Loading the dataset

In [2]:

```
df=pd.read_csv('/kaggle/input/google-playstore-apps/Google-Playstore.csv')
```

In [3]:

```
df.head()
```

Out[3]:

	App Name	App Id	Category	Rating	Rating Count	Installs
0	Gakondo	com.ishakwe.gakondo	Adventure	0.0	0.0	10+
1	Ampere Battery Info	com.webserveis.batteryinfo	Tools	4.4	64.0	5,000+
2	Vibook	com.doantiepvien.crm	Productivity	0.0	0.0	50+
3	Smart City Trichy Public Service Vehicles 17UC...	cst.stJoseph.ug17ucs548	Communication	5.0	5.0	10+
4	GROW.me	com.horodyski.grower	Tools	0.0	0.0	100+

5 rows × 24 columns

In [4]:
```
df.columns
```

Out[4]:
```
Index(['App Name', 'App Id', 'Category', 'Rating', 'Rating Count', 'Install
s',
       'Minimum Installs', 'Maximum Installs', 'Free', 'Price', 'Currency',
       'Size', 'Minimum Android', 'Developer Id', 'Developer Website',
       'Developer Email', 'Released', 'Last Updated', 'Content Rating',
       'Privacy Policy', 'Ad Supported', 'In App Purchases', 'Editors Choic
e',
       'Scraped Time'],
      dtype='object')
```

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

Out[5]:
```
(2312944, 24)
```

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2312944 entries, 0 to 2312943
Data columns (total 24 columns):
 #   Column             Dtype
---  ------             -----
 0   App Name           object
 1   App Id             object
 2   Category           object
 3   Rating             float64
 4   Rating Count       float64
 5   Installs           object
 6   Minimum Installs   float64
 7   Maximum Installs   int64
 8   Free               bool
 9   Price              float64
 10  Currency           object
 11  Size               object
 12  Minimum Android    object
 13  Developer Id       object
 14  Developer Website  object
 15  Developer Email    object
 16  Released           object
 17  Last Updated       object
 18  Content Rating     object
 19  Privacy Policy     object
 20  Ad Supported       bool
 21  In App Purchases   bool
 22  Editors Choice     bool
 23  Scraped Time       object
dtypes: bool(4), float64(4), int64(1), object(15)
memory usage: 361.8+ MB
```

In [7]:
```
df.describe()
```

Out[7]:

	Rating	Rating Count	Minimum Installs	Maximum Installs	Price
count	2.290061e+06	2.290061e+06	2.312837e+06	2.312944e+06	2.312944e+06
mean	2.203152e+00	2.864839e+03	1.834452e+05	3.202017e+05	1.034992e-01
std	2.106223e+00	2.121626e+05	1.513144e+07	2.355495e+07	2.633127e+00
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	0.000000e+00	0.000000e+00	5.000000e+01	8.400000e+01	0.000000e+00
50%	2.900000e+00	6.000000e+00	5.000000e+02	6.950000e+02	0.000000e+00
75%	4.300000e+00	4.200000e+01	5.000000e+03	7.354000e+03	0.000000e+00
max	5.000000e+00	1.385576e+08	1.000000e+10	1.205763e+10	4.000000e+02

Preprocessing the data

In [8]:

```
df.Size
```

Out[8]:

```
0           10M
1          2.9M
2          3.7M
3          1.8M
4          6.2M
           ...
2312939     77M
2312940     44M
2312941     29M
2312942     10M
2312943    5.2M
Name: Size, Length: 2312944, dtype: object
```

In [9]:

```
temp_size=[]
for x in df.Size:
    if  pd.isna(x):
        temp_size.append(np.nan)
    elif 'G' in x:
        temp_size.append(float(re.sub('G','',x))*1000)
    elif  'M' in x:
        temp_size.append(float(re.sub('M|,','',x)))
    elif 'K' in x or 'k' in x:
        temp_size.append(float(re.sub('K|k|,','',x))/1000.0)
    else:
        temp_size.append(0)

df.Size = temp_size
```

In [10]:

```
df.Size
```

Out[10]:
```
0          10.0
1           2.9
2           3.7
3           1.8
4           6.2
           ...
2312939    77.0
2312940    44.0
2312941    29.0
2312942    10.0
2312943     5.2
Name: Size, Length: 2312944, dtype: float64
```

In [11]:
```
df.Released
```

Out[11]:
```
0          Feb 26, 2020
1          May 21, 2020
2           Aug 9, 2019
3          Sep 10, 2018
4          Feb 21, 2020
               ...
2312939             NaN
2312940    Jan 17, 2018
2312941    Aug 19, 2018
2312942     Aug 1, 2016
2312943     Aug 9, 2019
Name: Released, Length: 2312944, dtype: object
```

In [12]:
```
Released = []
for x in df.Released:
    if  pd.isna(x):
        Released.append(np.nan)
    else:
        Released.append(datetime.strptime(x, '%b %d, %Y'))

df.Released = Released
```

In [13]:
```
df["Last Updated"]=pd.to_datetime(df["Last Updated"])
```

In [14]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2312944 entries, 0 to 2312943
Data columns (total 24 columns):
 #   Column             Dtype
---  ------             -----
 0   App Name           object
 1   App Id             object
 2   Category           object
 3   Rating             float64
 4   Rating Count       float64
 5   Installs           object
 6   Minimum Installs   float64
 7   Maximum Installs   int64
 8   Free               bool
 9   Price              float64
 10  Currency           object
 11  Size               float64
 12  Minimum Android    object
 13  Developer Id       object
 14  Developer Website  object
 15  Developer Email    object
 16  Released           datetime64[ns]
 17  Last Updated       datetime64[ns]
 18  Content Rating     object
 19  Privacy Policy     object
 20  Ad Supported       bool
 21  In App Purchases   bool
 22  Editors Choice     bool
 23  Scraped Time       object
dtypes: bool(4), datetime64[ns](2), float64(5), int64(1), object(12)
memory usage: 361.8+ MB
```

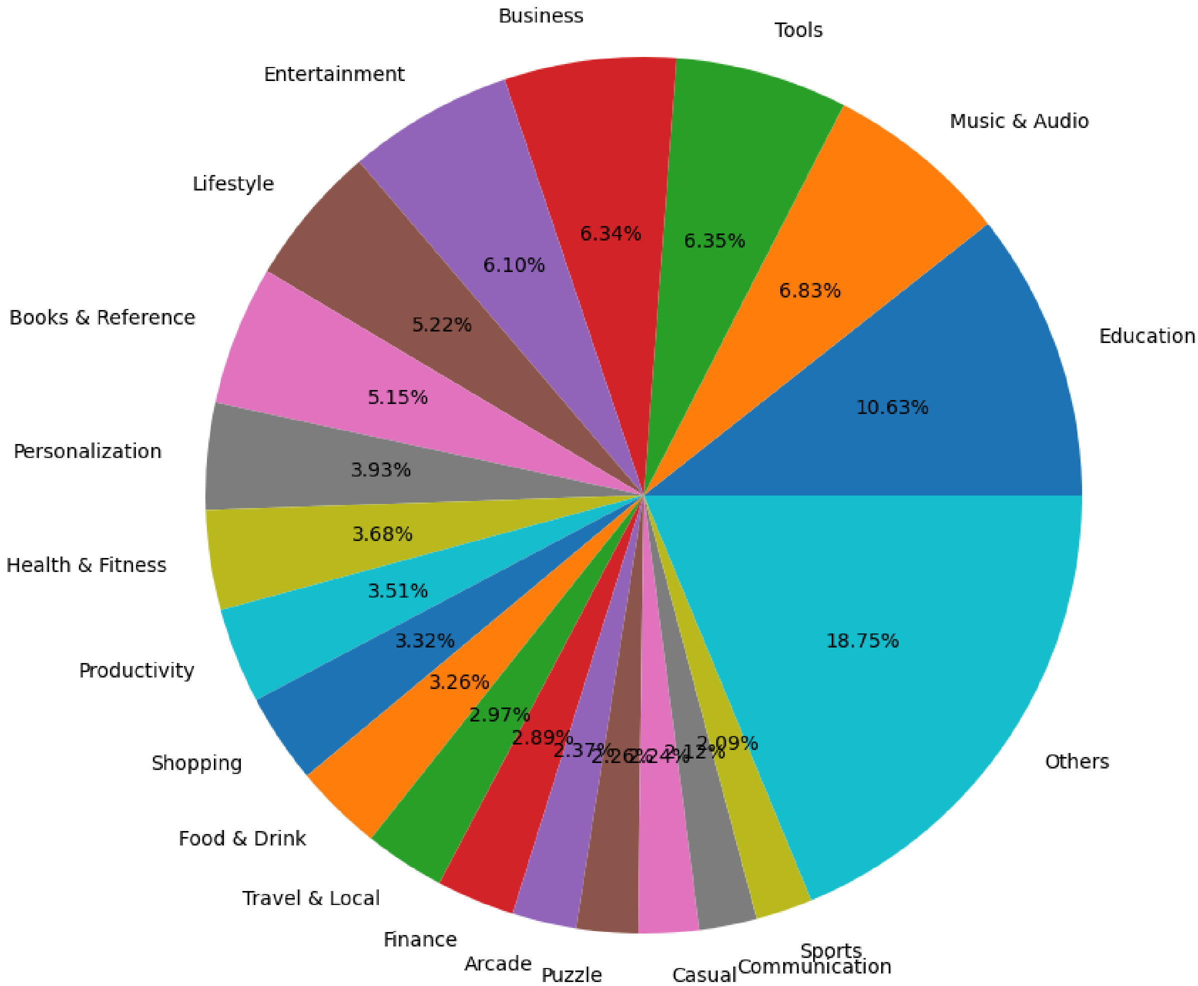
Extracting Insights

The first 20 Category App

In [15]:
```
pie_data = df.Category.value_counts()
```

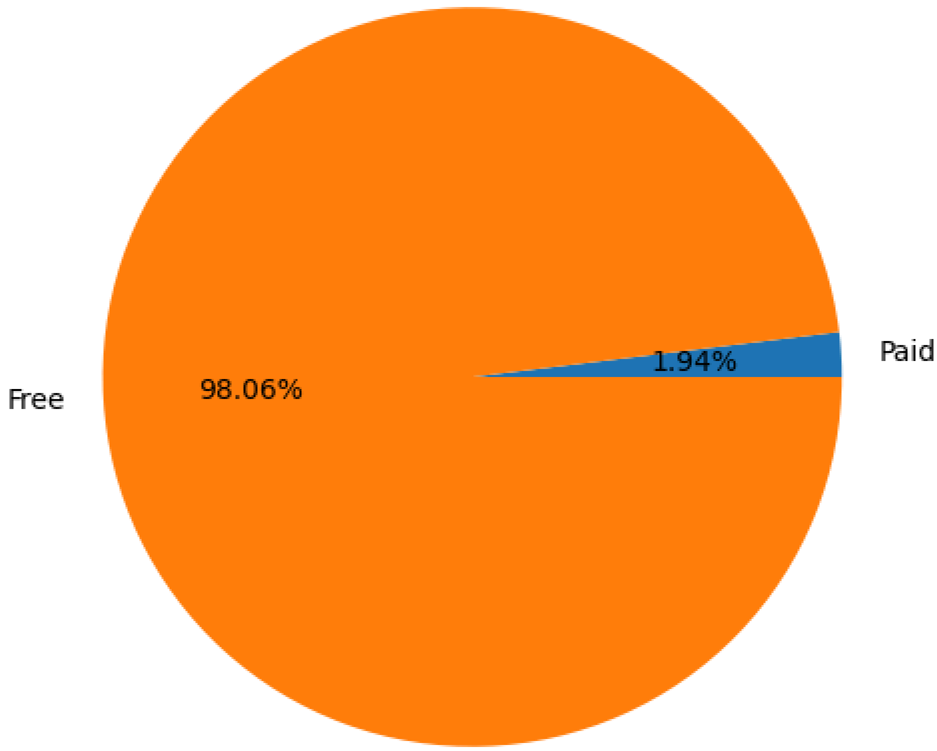
In [16]:
```
graph_data = pie_data[:19]
graph_data["Others"] = pie_data[20:].sum()
```

In [17]:
```
plt.pie(graph_data.values, labels=graph_data.keys(), autopct='%1.2f%%')
plt.show()
```



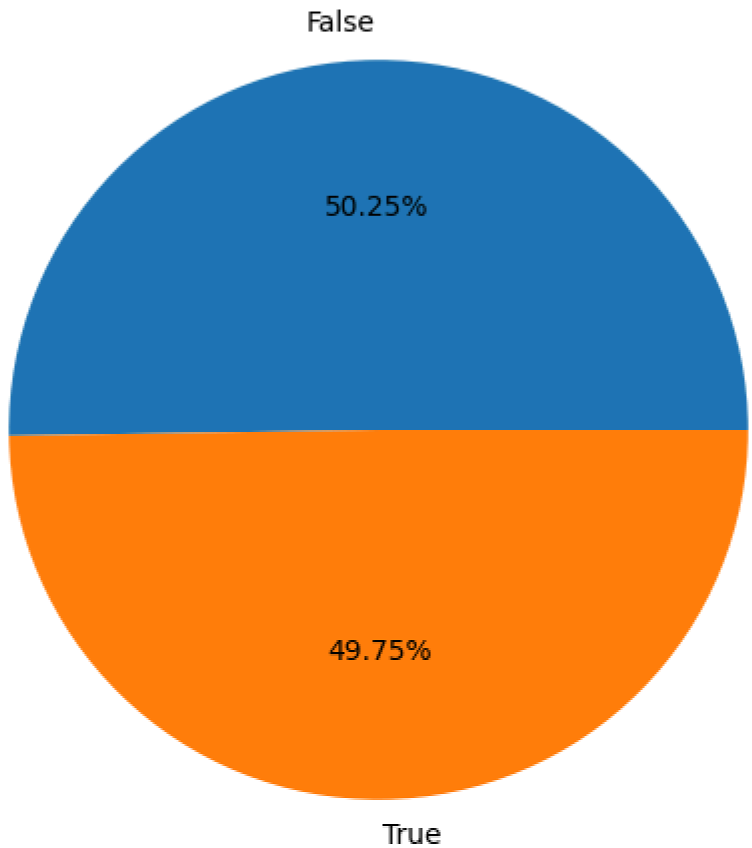
Free vs Paid

In [18]:
```
paid_free_data = {
    "Paid": df.Price[df.Price > 0].count(),
    "Free": df.Price[df.Price == 0].count()
}
plt.figure(figsize=(6,6))
plt.pie(paid_free_data.values(), labels=paid_free_data.keys(), autopct='%1.2
plt.show()
```



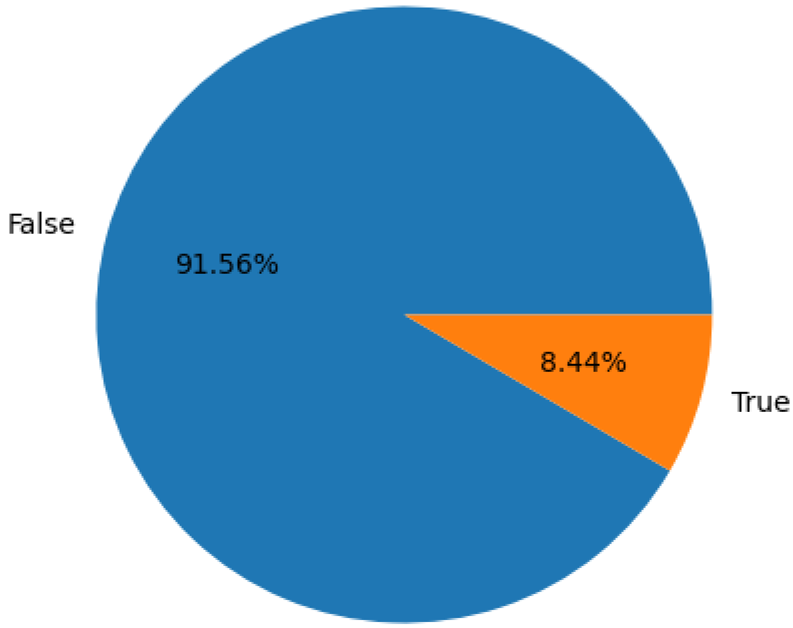
Add Supported App

In [20]:
```
ad_supported=df["Ad Supported"].value_counts()
plt.figure(figsize=(6,6))
plt.pie(ad_supported.values, labels=ad_supported.keys(), autopct='%1.2f%%')
plt.show()
```



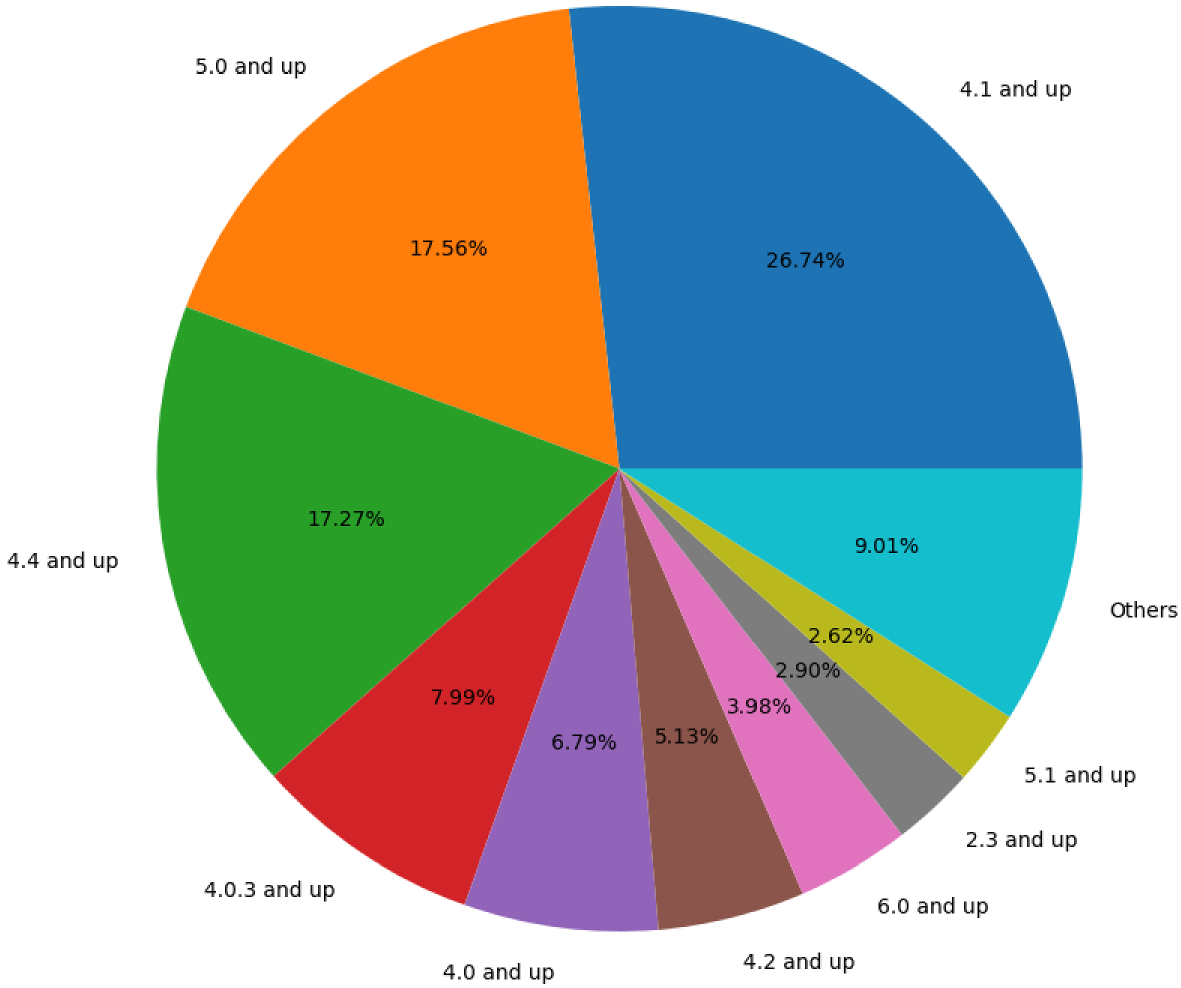
Purchase Option in App

In [21]:
```
app_purchase = df["In App Purchases"].value_counts()
plt.figure(figsize=(5,5))
plt.pie(app_purchase.values, labels=app_purchase.keys(), autopct='%1.2f%%')
plt.show()
```



Top 10 Minimum Android version

In [22]:
```
android_version = df["Minimum Android"].value_counts()

graph_data = android_version[:9]
graph_data["Others"] = android_version[10:].sum()
plt.figure(figsize=(10,10))
plt.pie(graph_data.values, labels=graph_data.keys(), autopct='%1.2f%%')
plt.show()
```



Top 10 most expensive App

In [23]:
```
sorted_df = df.sort_values(by=['Price'], ascending=False)
```

In [24]:
```
sorted_df2=sorted_df.set_index('App Name')
```

In [25]:
```
sorted_df2[["Category","Rating","Maximum Installs","Price"]][0:10]
```

Out[25]:

App Name	Category	Rating	Maximum Installs	Price
MESH Connect	Productivity	0.0	25	400.00
AudD	Music & Audio	3.2	4397	399.99
RichWall	Social	0.0	0	399.99
TEST EGY	Tools	0.0	0	399.99
Premium Luxury Watches - Luxury Watches Brands	Shopping	0.0	18	399.99
I'm Rich - VIP Club Limited	Business	0.0	0	399.99
Acid Reflux Treatment	Health & Fitness	0.0	1	399.99
Most expensive word game	Board	3.4	5523	399.99
Plasma duct - Premium Game	Puzzle	3.5	3369	399.99
My Money	Tools	0.0	0	399.99

Top 10 Maximum Installs App Table

In [26]:

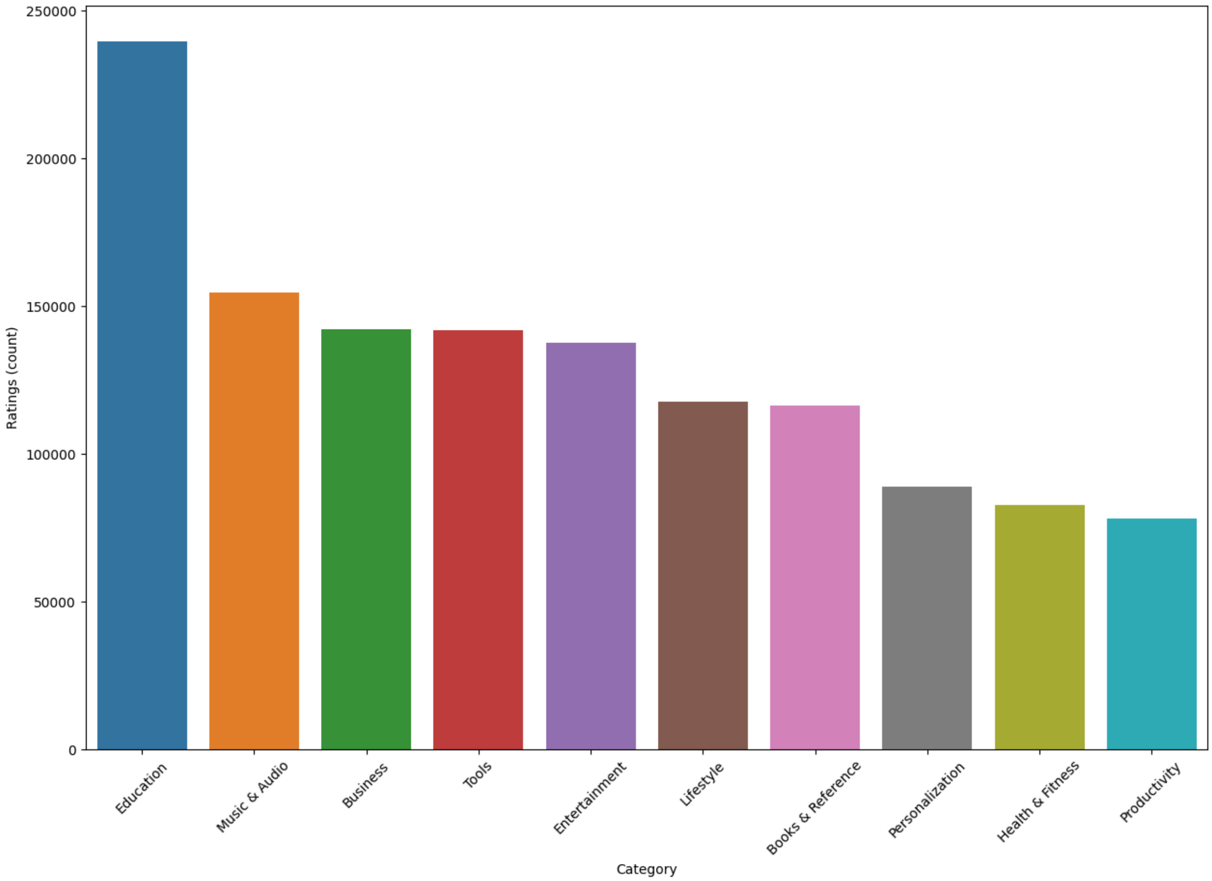
```
sorted_Install= df.sort_values(by=['Maximum Installs'], ascending=False)
HTML(sorted_Install[["App Name","Category","Rating","Price","Maximum Install
```

Out[26]:

App Name	Category	Rating	Price	Maximum Installs
Google Play services	Tools	4.2	0.0	12057627016
YouTube	Video Players & Editors	4.4	0.0	9766230924
Google	Tools	4.2	0.0	9154248491
Google Maps - Navigate & Explore	Travel & Local	3.8	0.0	9141671889
Google Text-to-Speech	Tools	4.1	0.0	9034404884
Google Chrome: Fast & Secure	Communication	4.1	0.0	8925640788
Gmail	Communication	4.2	0.0	8756574289
Android Accessibility Suite	Tools	4.2	0.0	7408134567
Google Drive	Productivity	4.3	0.0	7028265259
Facebook	Social	2.3	0.0	6782619635

The most Rated top 10 Category

```
In [27]: a = df.groupby(["Category"])["Rating"].count().sort_values(ascending=False)[
         ax = sns.barplot(x=a.keys(), y=a.values)
         ax.tick_params(axis='x', labelrotation = 45)
         ax = plt.ylabel('Ratings (count)')
```

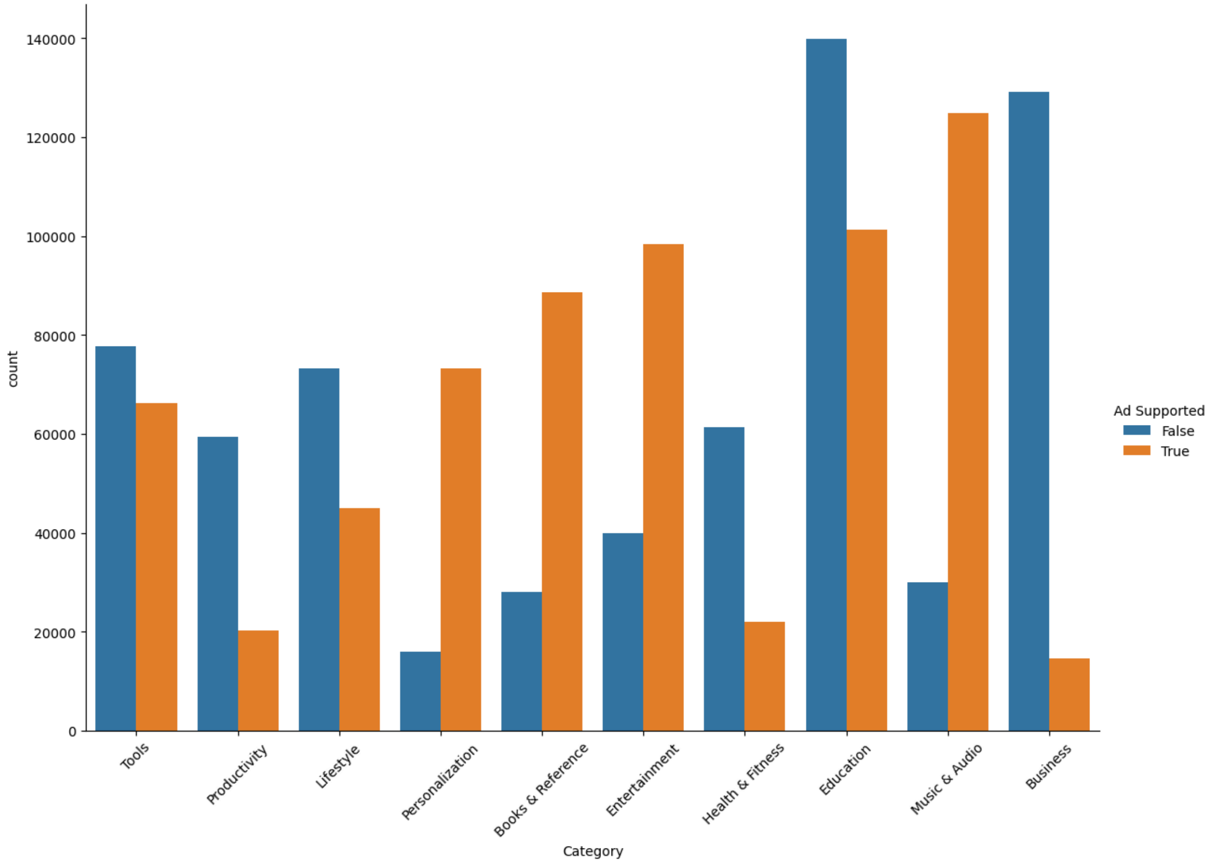


Top 10 category with Ad Supported¶

```
In [28]: topTenCategoriesNames=df["Category"].value_counts()[0:10].keys()
```

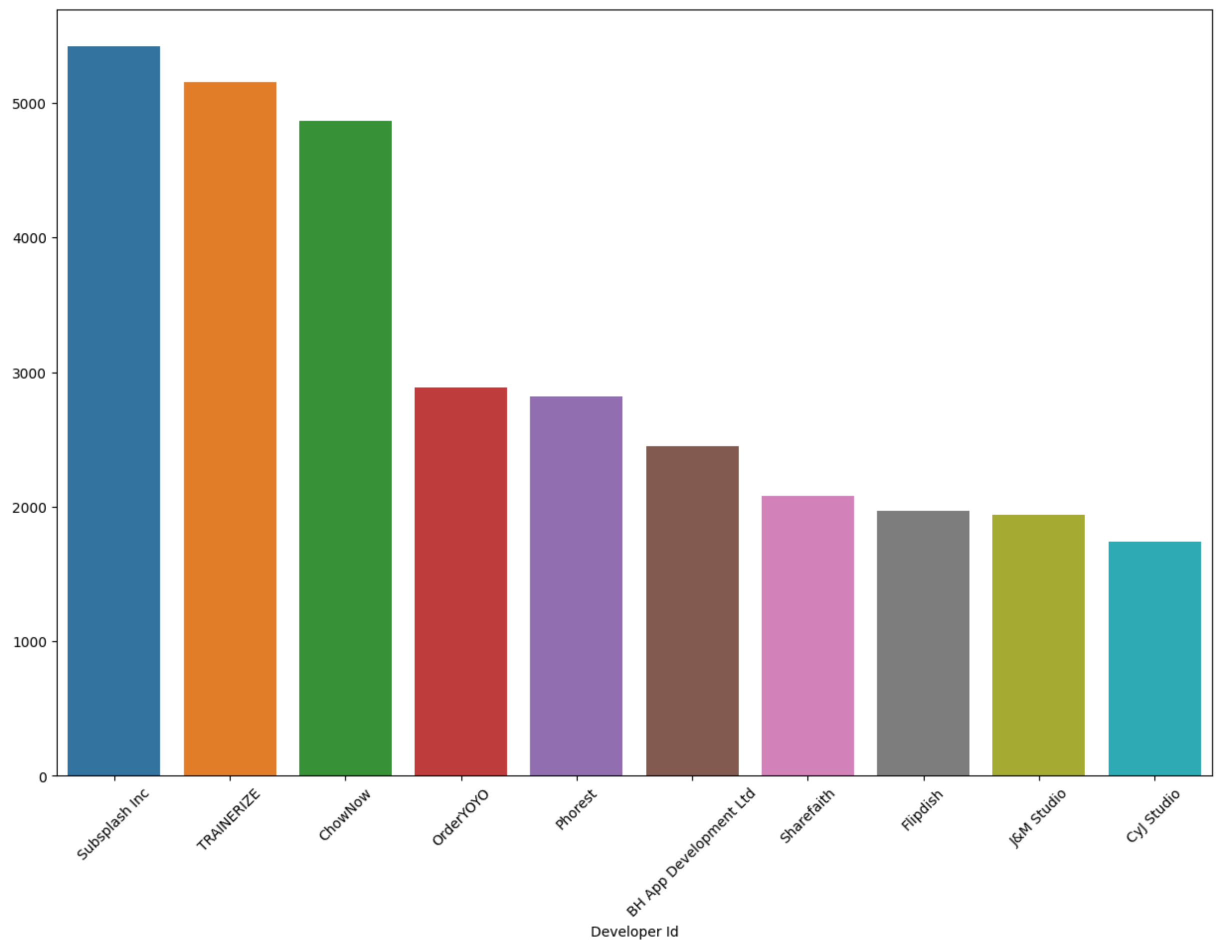
```
In [29]: a = df[df.Category.isin(topTenCategoriesNames)]
         ax = sns.catplot(data=a,kind="count", x="Category", hue="Ad Supported",heigh
         ax.set_xticklabels(rotation= 45)
```

```
Out[29]: <seaborn.axisgrid.FacetGrid at 0x7dd81c2d8c10>
```



Top 10 Developer

In [30]:
```
topTenDeveloperID= df["Developer Id"].value_counts()[0:10]
ax = sns.barplot(x=topTenDeveloperID.keys() , y=topTenDeveloperID.values)
ax.tick_params(axis='x', labelrotation = 45)
```

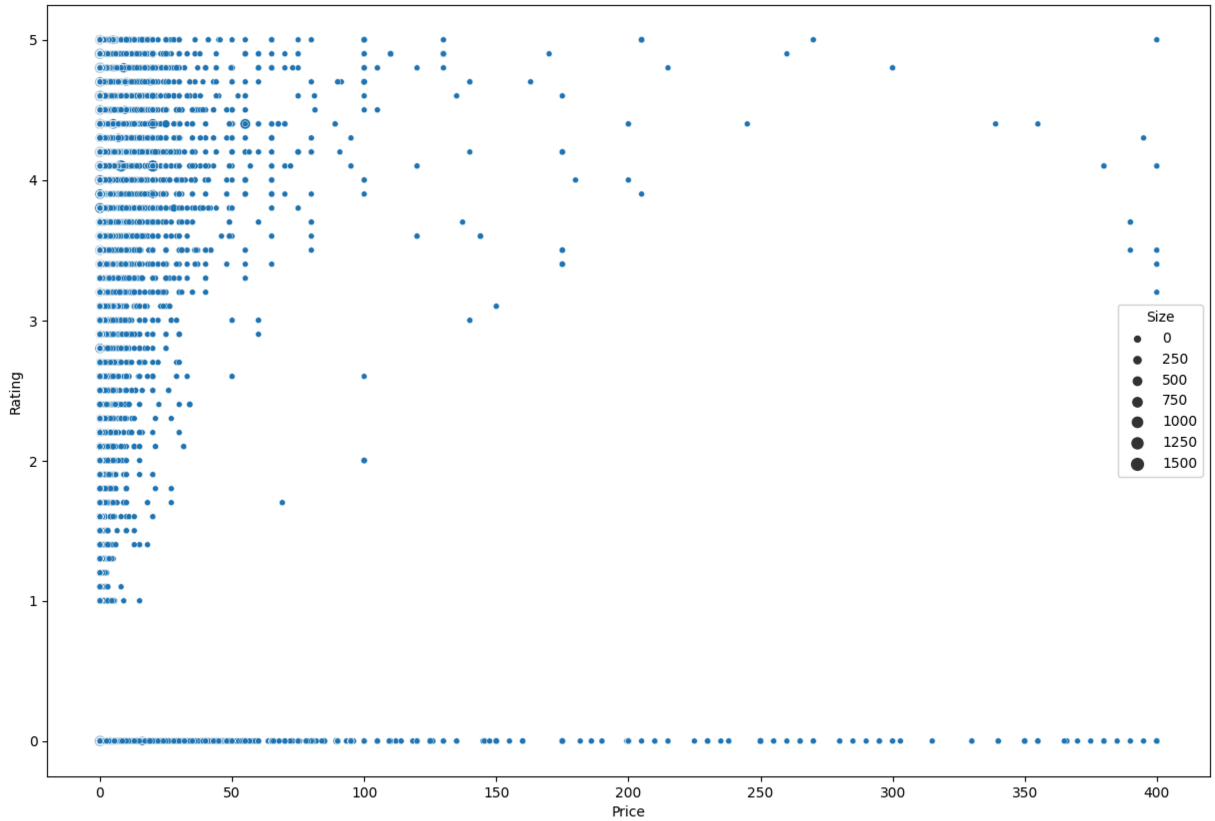


In [31]:

```
sns.scatterplot( data=df, x="Price", y="Rating", size=df["Size"],)
```

Out[31]:

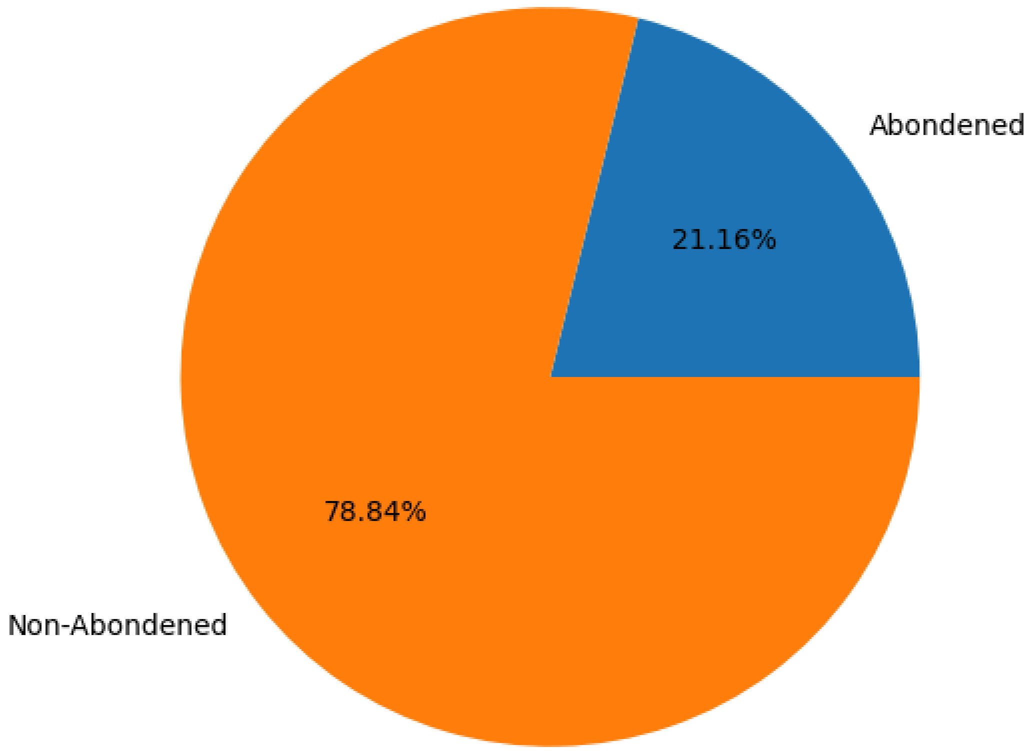
```
<Axes: xlabel='Price', ylabel='Rating'>
```



Abondened & Non-Abondened App before 2019

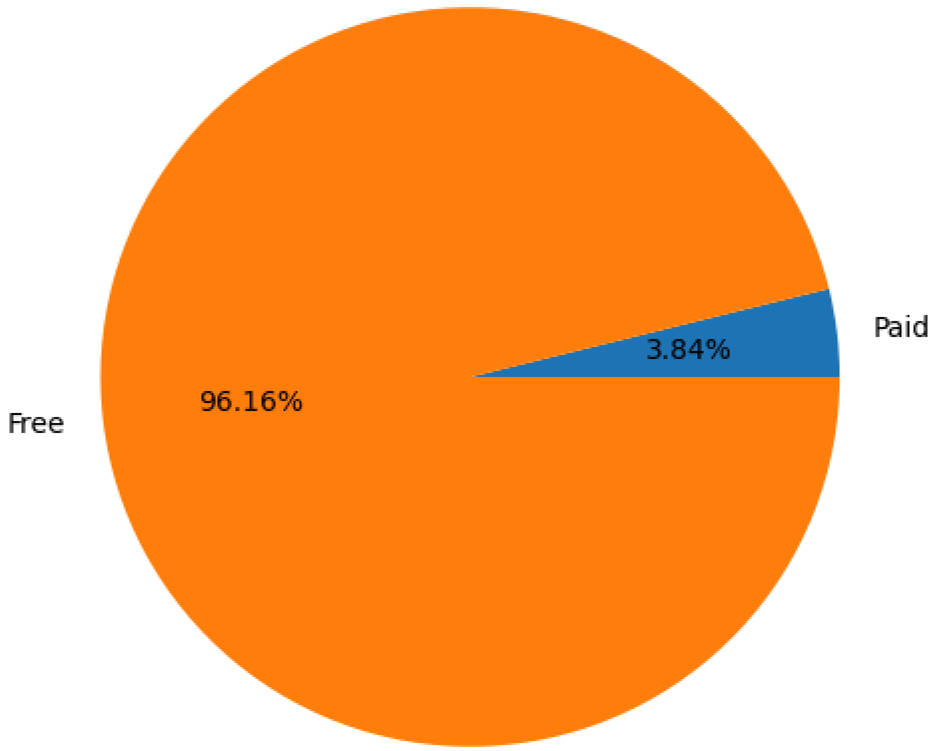
In [32]:

```
app = {
    "Abondened":(df[df["Last Updated"]<"2019"]).shape[0] ,
    "Non-Abondened":(df[df["Last Updated"]>="2019"]).shape[0]
}
plt.figure(figsize=(6,6))
ax = plt.pie(app.values(), labels=app.keys(), autopct='%1.2f%%')
```



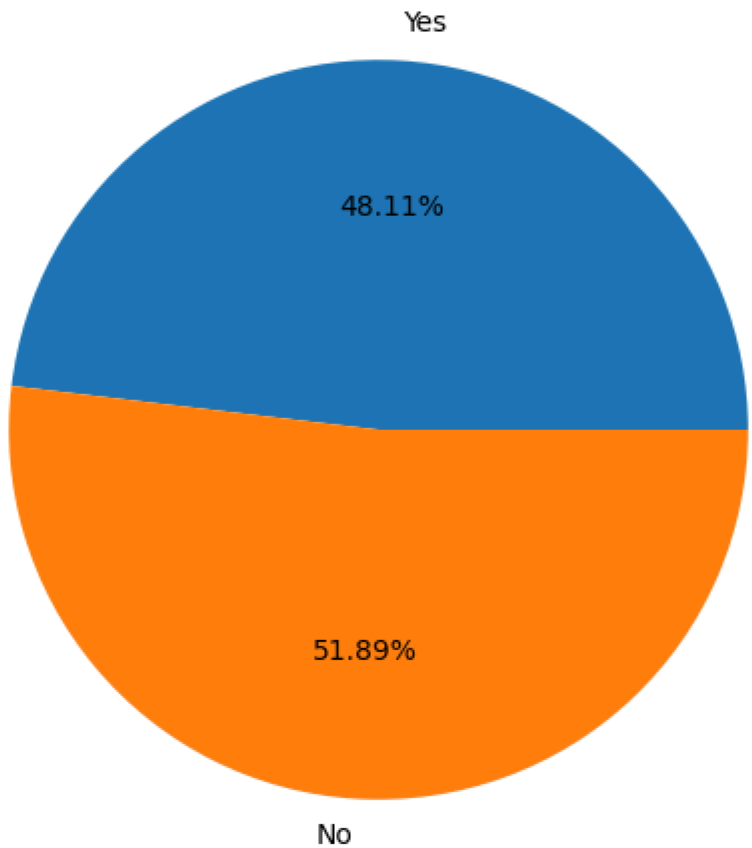
Free & Paid in Abondened App

In [33]:
```
abondened = df[df["Last Updated"]<"2019"]

abondened_paid_free = {
    "Paid": abondened.Price[abondened.Price > 0].count(),
    "Free": abondened.Price[abondened.Price == 0].count()
}
plt.figure(figsize=(6,6))
ax = plt.pie(abondened_paid_free.values(), labels=abondened_paid_free.keys()
```



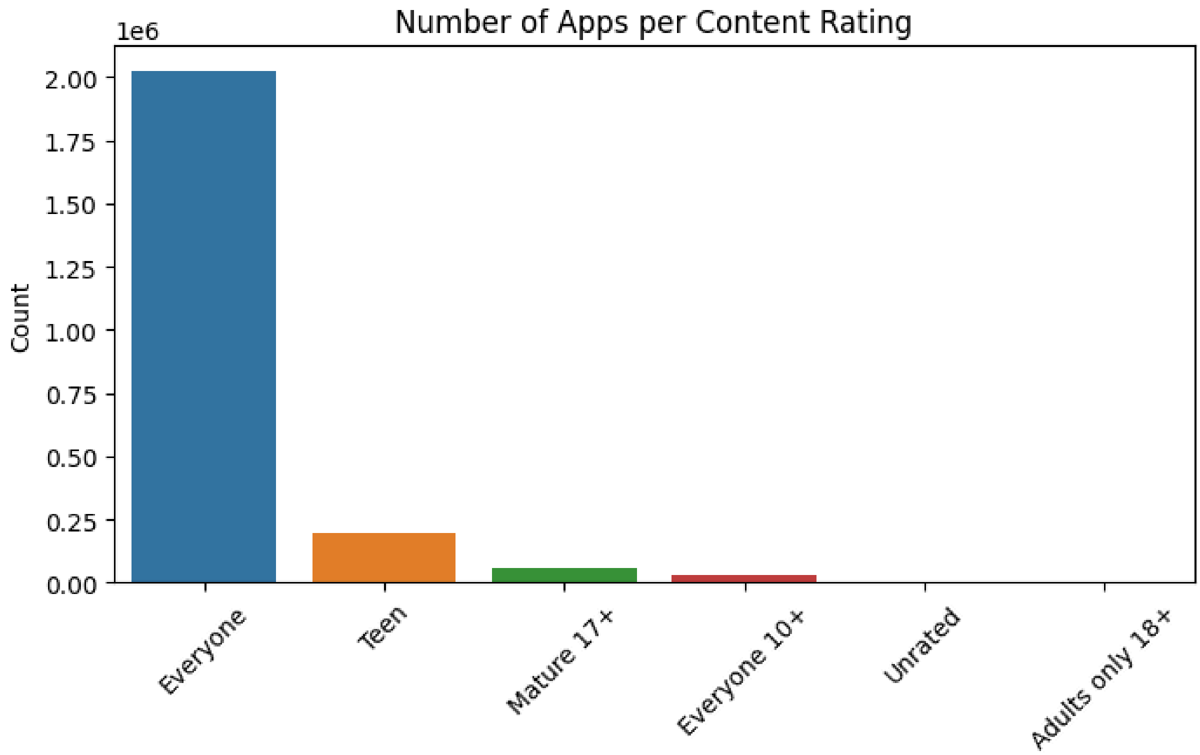
Ad Supported in Abondened App

In [34]:
```
abondened = df[df["Last Updated"]<"2019"]

abondened_ad_supported = {

    "Yes": abondened["Ad Supported"][abondened["Ad Supported"] == True].cour
    "No" : abondened["Ad Supported"][abondened["Ad Supported"] == False].cou
}
plt.figure(figsize=(6,6))
ax = plt.pie(abondened_ad_supported.values(), labels=abondened_ad_supported.
```



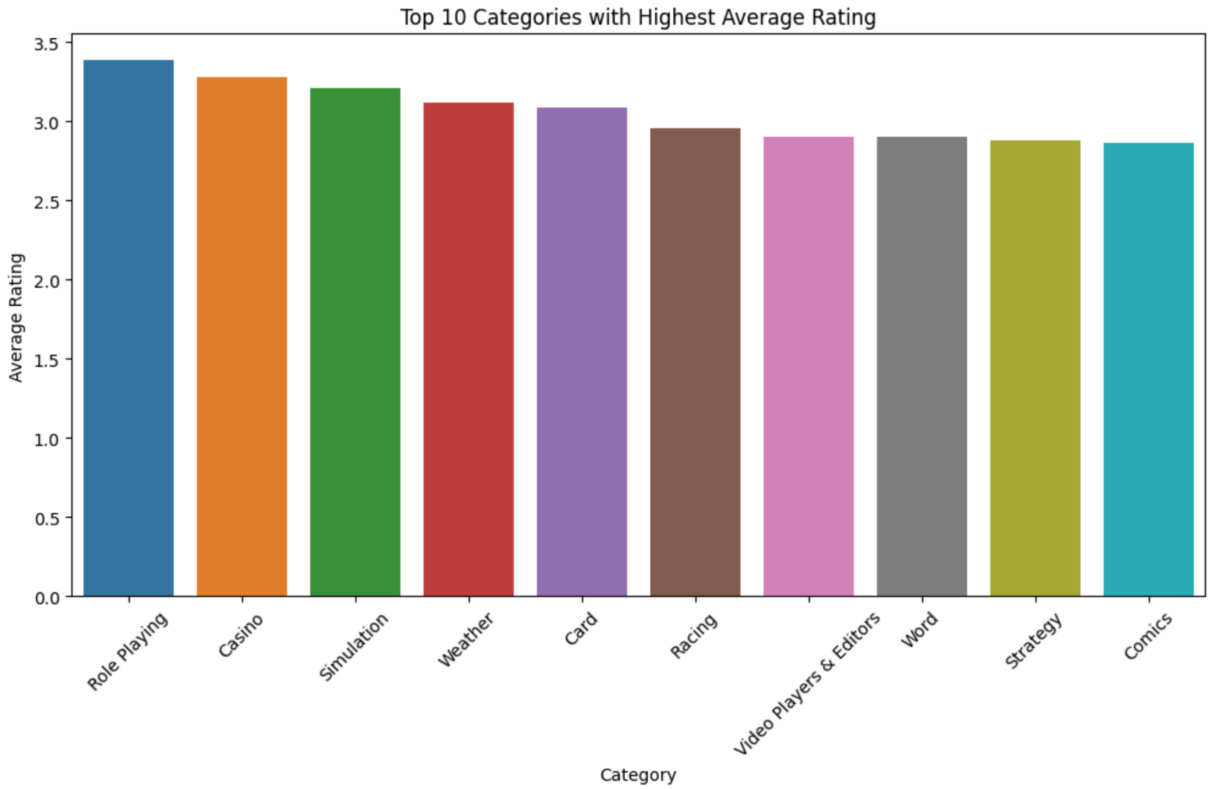
Number of Apps per Content Rating

In [35]:
```
#Visualize the distribution of content ratings
plt.figure(figsize=(8, 4))
sns.countplot(x='Content Rating', data=df, order=df['Content Rating'].value_
plt.title('Number of Apps per Content Rating')
plt.xlabel('Content Rating')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.show()
```



Top 10 Categories with Highest Average Rating

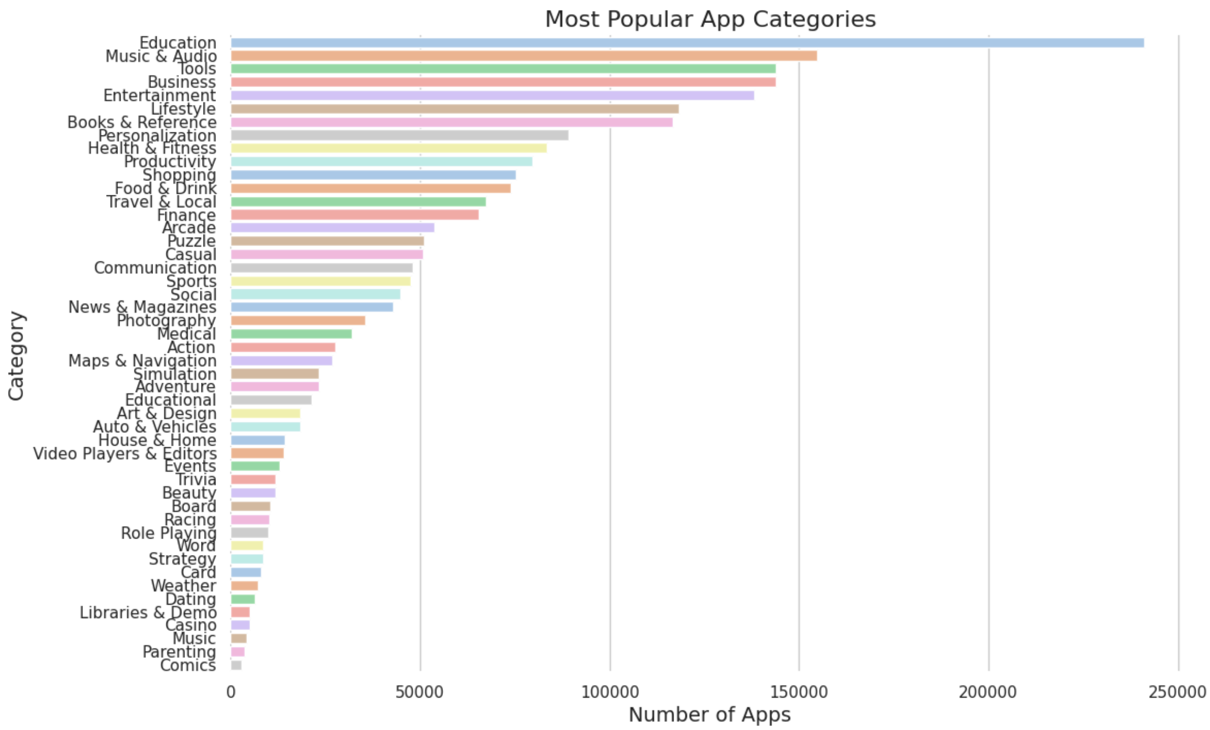
In [36]:
```
#Visualize the top 10 categories with the highest average rating
### What are the most popular app categories in terms of the number of apps
top_categories = df.groupby('Category')['Rating'].mean().sort_values(ascendi

plt.figure(figsize=(12, 6))
sns.barplot(x=top_categories.index, y=top_categories.values)
plt.title('Top 10 Categories with Highest Average Rating')
plt.xlabel('Category')
plt.ylabel('Average Rating')
plt.xticks(rotation=45)
plt.show()
```



What are the most popular app categories in terms of the number of apps available?

In [37]:

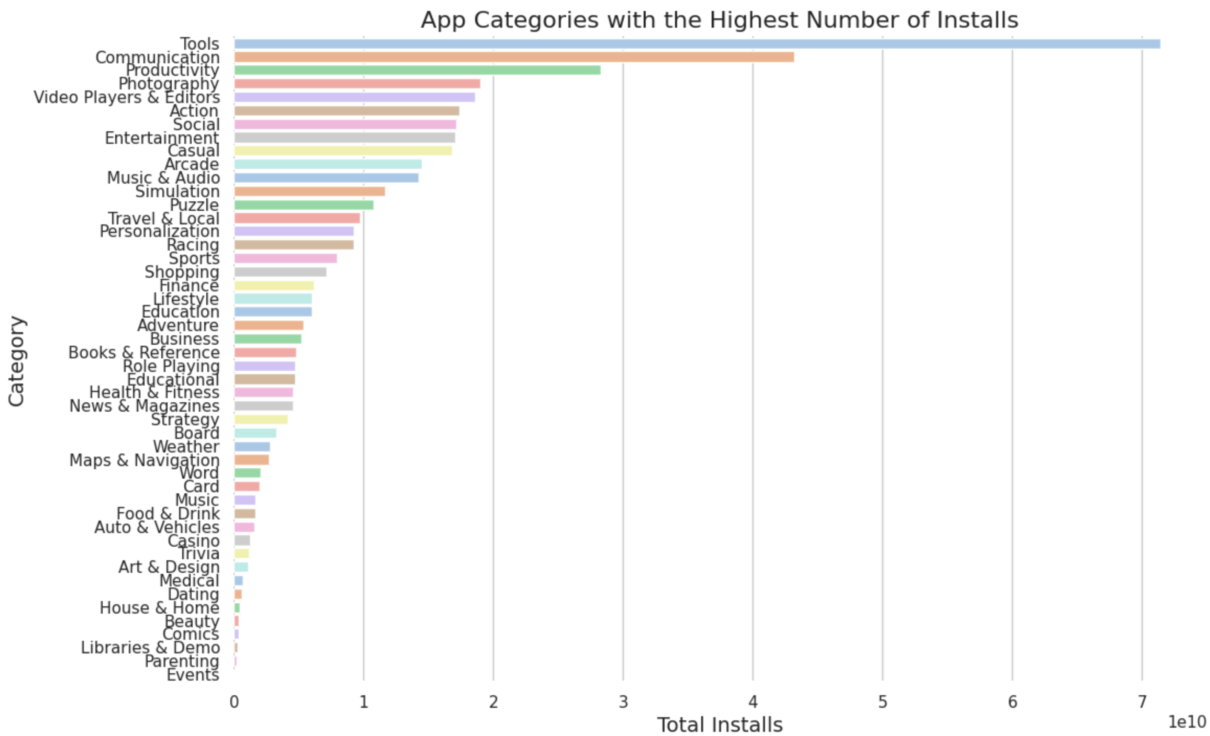
```
# Assuming the dataset is loaded as 'data'
category_counts = df['Category'].value_counts()


# Set the color palette and minimal style
sns.set(style="whitegrid", palette="pastel")

# Create the plot
plt.figure(figsize=(12, 8))
sns.barplot(x=category_counts.values, y=category_counts.index, palette="past

# Customize the plot
plt.title('Most Popular App Categories', fontsize=16)
plt.xlabel('Number of Apps', fontsize=14)
plt.ylabel('Category', fontsize=14)

# Remove unnecessary plot elements
sns.despine(left=True, bottom=True)

# Show the plot
plt.show()
```



Which app categories have the highest number of installs?

In [38]:

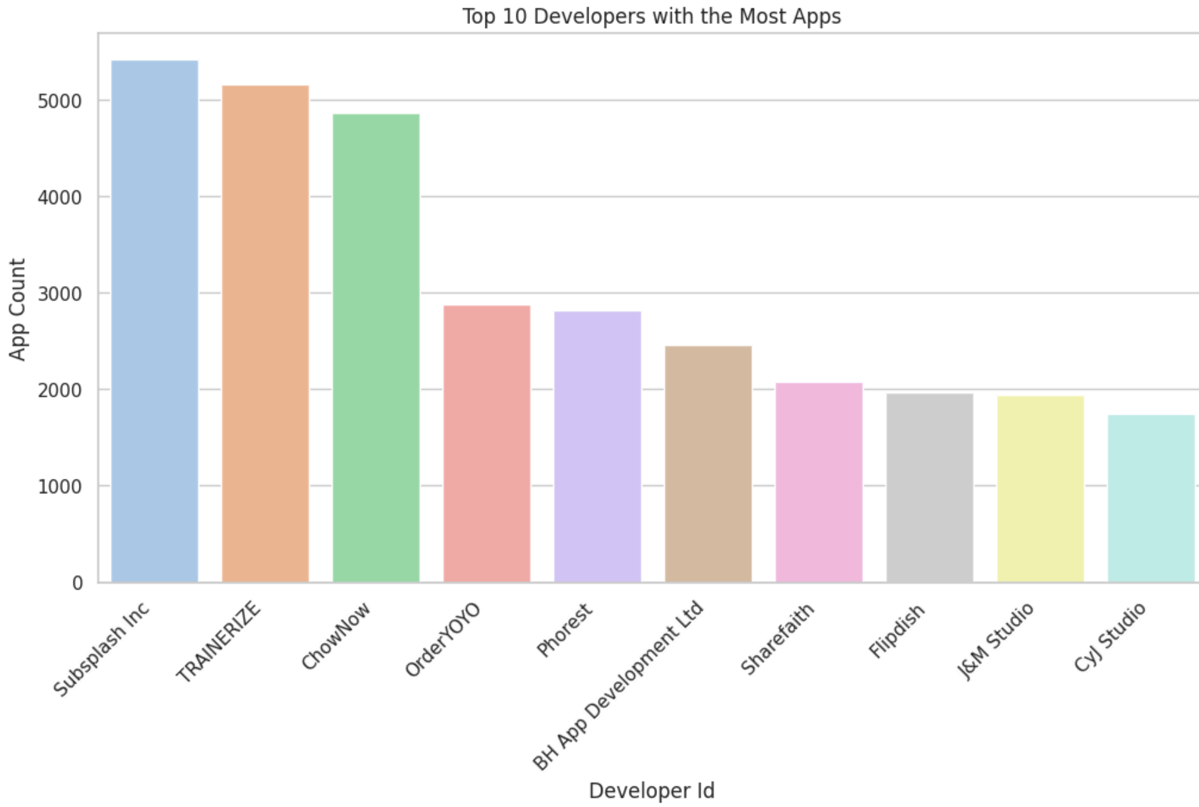
```
# Clean up the 'Installs' column
df['Installs_clean'] = df['Installs'].str.replace('[^0-9]', '', regex=True).

# Calculate the total installs per category
category_installs = df.groupby('Category')['Installs_clean'].sum().sort_valu

# Set the color palette and minimal style
sns.set(style="whitegrid", palette="pastel")

# Create the plot
plt.figure(figsize=(12, 8))
sns.barplot(x=category_installs.values, y=category_installs.index, palette="

# Customize the plot
plt.title('App Categories with the Highest Number of Installs', fontsize=16)
plt.xlabel('Total Installs', fontsize=14)
plt.ylabel('Category', fontsize=14)

# Remove unnecessary plot elements
sns.despine(left=True, bottom=True)

# Show the plot
plt.show()
```



Which app developers have the most apps in the dataset, and do they have any common characteristics?

In [39]:

```
# Group the dataset by Developer Id and calculate the mean rating, app count
developer_stats = df.groupby('Developer Id').agg({'App Name': 'count', 'Rati

# Sort the results by app count in descending order
sorted_developer_stats = developer_stats.sort_values('App Count', ascending=

# Visualize the top 10 developers with the most apps
plt.figure(figsize=(12, 6))
sns.barplot(x=sorted_developer_stats.head(10).index, y=sorted_developer_stat
plt.title('Top 10 Developers with the Most Apps')
plt.xlabel('Developer Id')
plt.ylabel('App Count')
plt.xticks(rotation=45, ha='right')
plt.show()

# Display common characteristics for the top 10 developers with the most app
top_developers = sorted_developer_stats.head(10)
print("Common Characteristics for Top 10 Developers with the Most Apps:")
print("Mean Rating: {:.2f}".format(top_developers['Rating'].mean()))
print("Mean App Size (MB): {:.2f}".format(top_developers['Size'].mean()))
print("Mean Installs: {:.0f}".format(top_developers['Installs_clean'].mean()
```




```
Common Characteristics for Top 10 Developers with the Most Apps:
Mean Rating: 0.38
Mean App Size (MB): 31.55
Mean Installs: 182
```

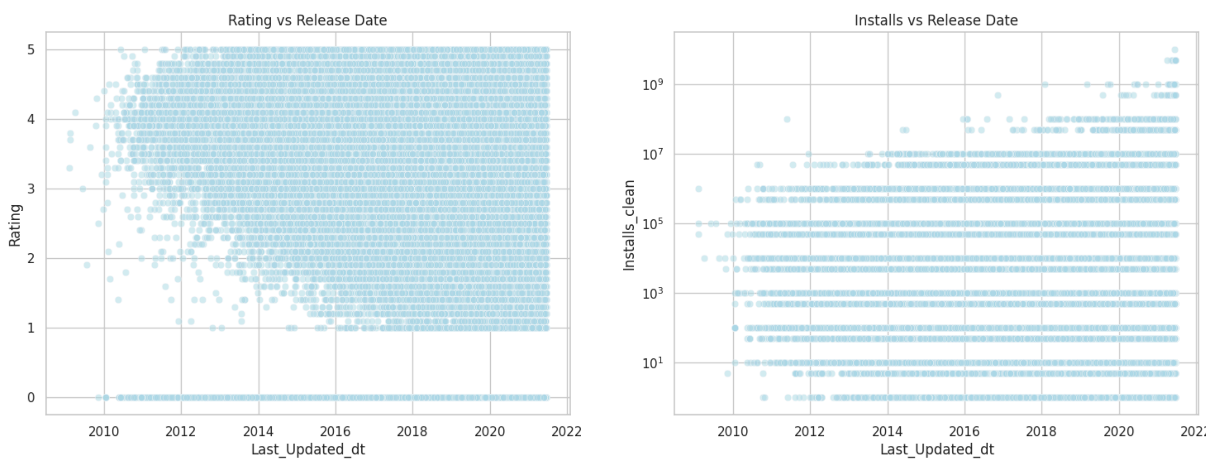
Is there a relationship between the app's release date and its rating or number of installs?

In [40]:

```
import matplotlib.dates as mdates

# Convert 'Last Updated' to datetime format
df['Last_Updated_dt'] = pd.to_datetime(df['Last Updated'])

# Convert datetime to the number of days since the earliest date
df['Days_Since_Updated'] = (df['Last_Updated_dt'] - df['Last_Updated_dt'].mi

# Calculate the correlation
rating_date_corr = df['Rating'].corr(df['Days_Since_Updated'])
installs_date_corr = df['Installs_clean'].corr(df['Days_Since_Updated'])

print("Correlation between Release Date and Rating: {:.2f}".format(rating_da
print("Correlation between Release Date and Installs: {:.2f}".format(install
def interpret_correlation(corr):
    if corr > 0.7:
        return "strong positive correlation"
    elif 0.5 <= corr <= 0.7:
        return "moderate positive correlation"
    elif 0.3 <= corr < 0.5:
        return "weak positive correlation"
    elif -0.3 <= corr < 0.3:
        return "no or negligible correlation"
```

```
    elif -0.5 <= corr < -0.3:
        return "weak negative correlation"
    elif -0.7 <= corr < -0.5:
        return "moderate negative correlation"
    else:
        return "strong negative correlation"

rating_corr_interpretation = interpret_correlation(rating_date_corr)
installs_corr_interpretation = interpret_correlation(installs_date_corr)

print("The relationship between Release Date and Rating shows a", rating_cor
print("The relationship between Release Date and Installs shows a", installs


# Visualize the results
fig, ax = plt.subplots(1, 2, figsize=(18, 6))

sns.scatterplot(data=df, x='Last_Updated_dt', y='Rating', alpha=0.5, ax=ax[0
ax[0].set_title('Rating vs Release Date')
ax[0].xaxis.set_major_formatter(mdates.DateFormatter('%Y'))

sns.scatterplot(data=df, x='Last_Updated_dt', y='Installs_clean', alpha=0.5,
ax[1].set_title('Installs vs Release Date')
ax[1].xaxis.set_major_formatter(mdates.DateFormatter('%Y'))
ax[1].set_yscale("log")

plt.show()
```

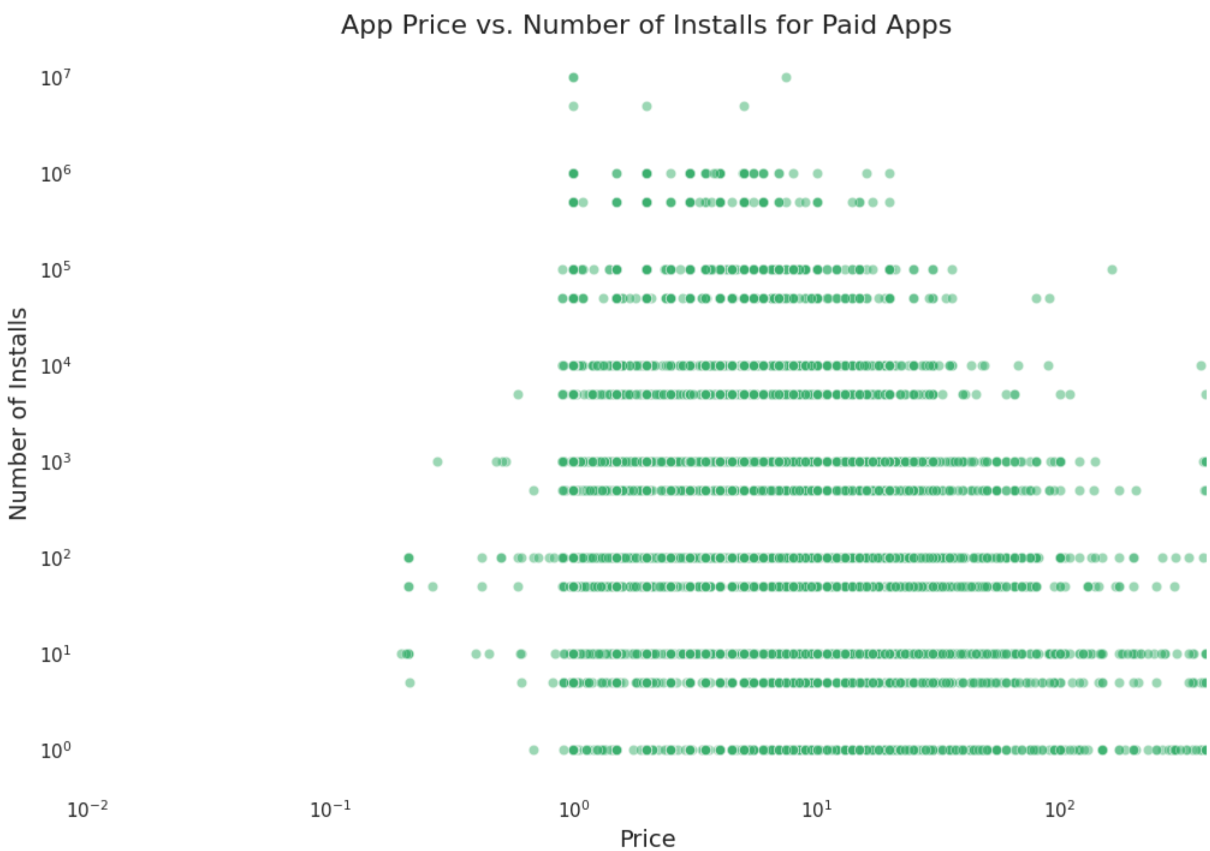
```
Correlation between Release Date and Rating: -0.02
Correlation between Release Date and Installs: 0.01
The relationship between Release Date and Rating shows a no or negligible co
rrelation
The relationship between Release Date and Installs shows a no or negligible
correlation
```



How does the app price affect the number of installs for paid apps?

In [41]:
```
# Filter paid apps
paid_apps = df[(df['Free'] == False)]
```

```python
# Set the color palette and minimal style
sns.set(style="white", palette="pastel")

# Create the plot
plt.figure(figsize=(12, 8))
sns.scatterplot(data=paid_apps, x="Price", y="Installs_clean", alpha=0.5, cc

# Customize the plot
plt.title('App Price vs. Number of Installs for Paid Apps', fontsize=16)
plt.xlabel('Price', fontsize=14)
plt.ylabel('Number of Installs', fontsize=14)
plt.xscale("log")
plt.yscale("log")
plt.xlim(0.01, paid_apps["Price"].max())

# Remove unnecessary plot elements
sns.despine(left=True, bottom=True)

# Show the plot
plt.show()
```



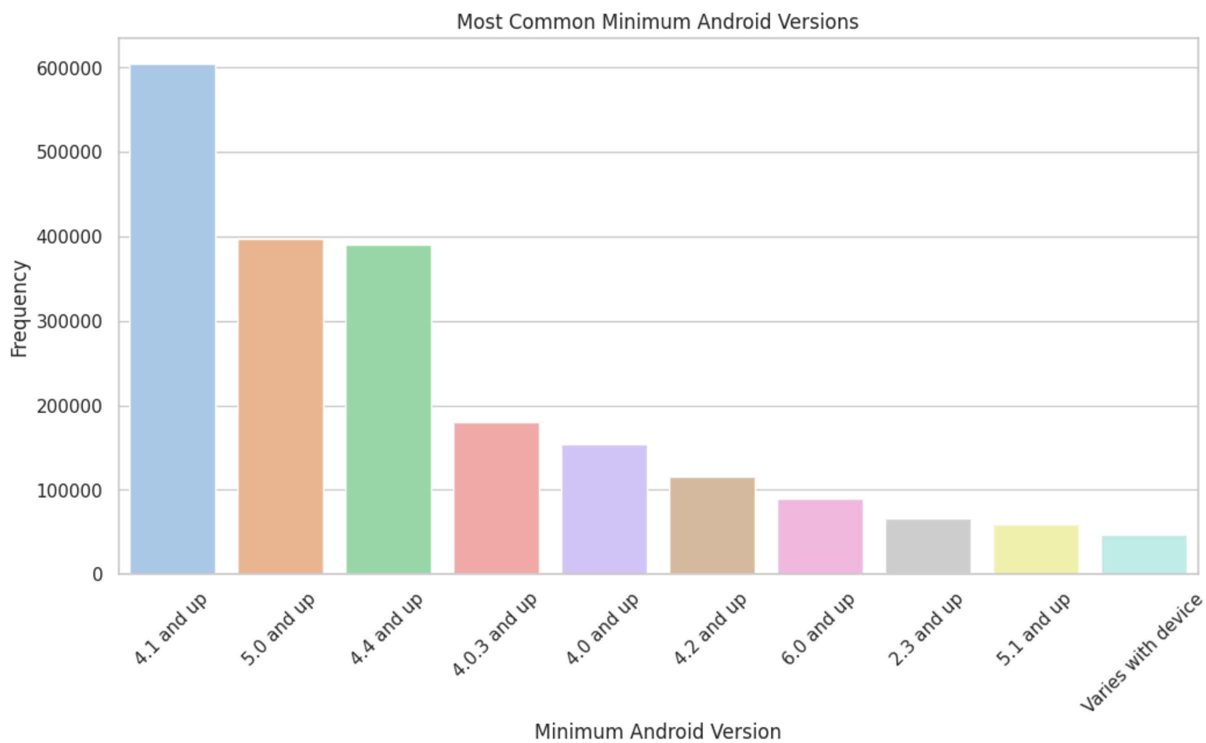
What are the most common minimum Android version requirements for apps, and does it affect the number of installs?

In [42]:

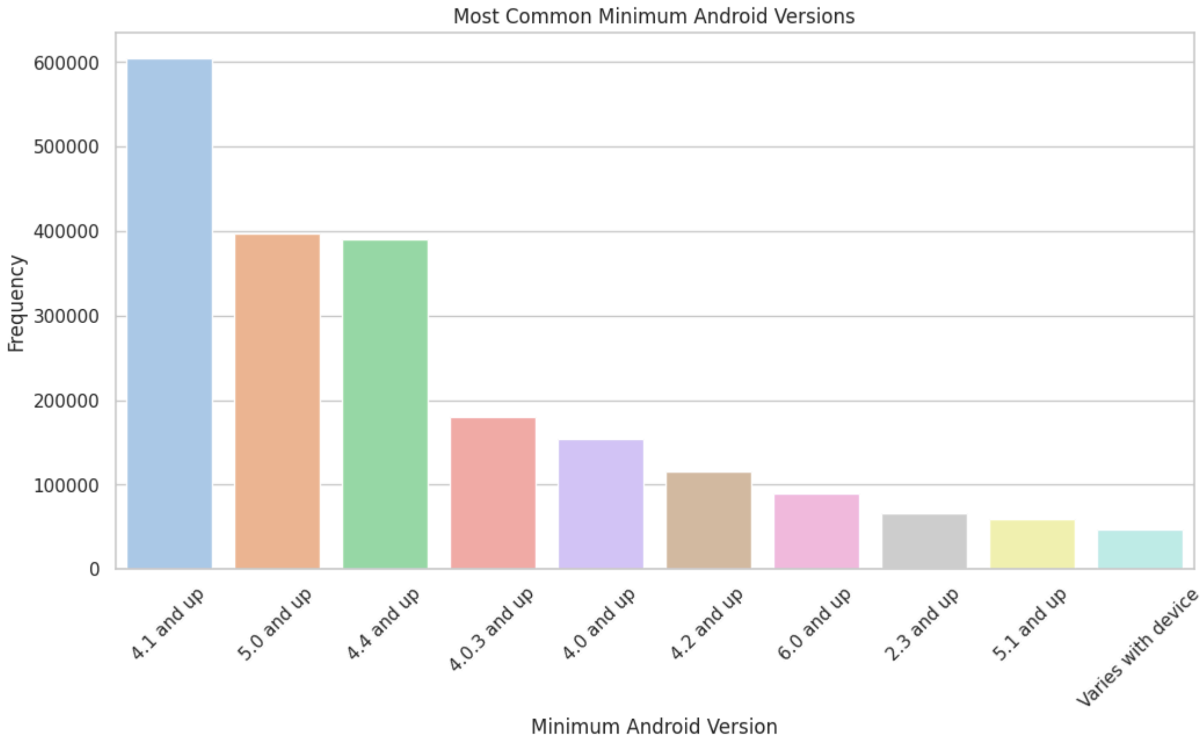
```python
# Count the frequency of each minimum Android version
min_android_counts = df['Minimum Android'].value_counts().head(10)
```

```
# Calculate the total number of installs for each minimum Android version
min_android_installs = df.groupby('Minimum Android')['Installs_clean'].sum()

# Create a DataFrame with counts and installs
min_android_df = pd.DataFrame({'Counts': min_android_counts, 'Total Installs
```

In [43]:
```
# Create a bar plot for the most common minimum Android versions
plt.figure(figsize=(12, 6))
sns.set_style("whitegrid")
sns.set_palette("pastel")
ax = sns.barplot(x=min_android_df.index, y='Counts', data=min_android_df)
plt.title('Most Common Minimum Android Versions')
plt.xlabel('Minimum Android Version')
plt.ylabel('Frequency')
plt.xticks(rotation=45)
plt.show()
```



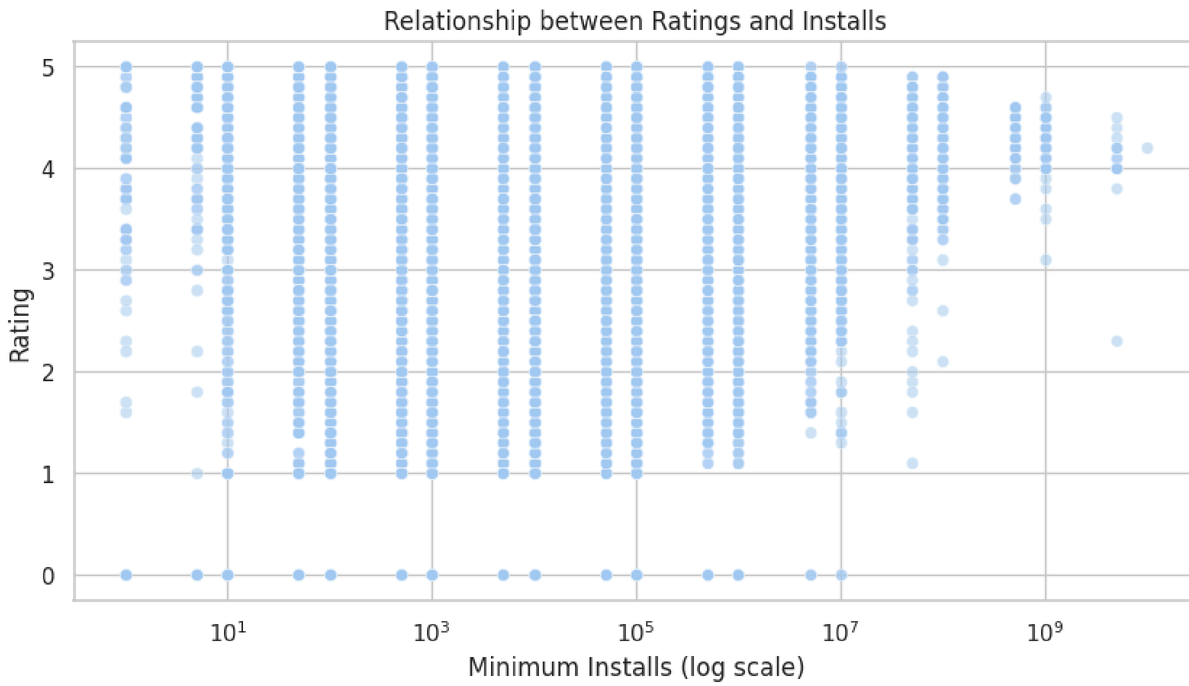
In [44]:
```
# Create a bar plot for the most common minimum Android versions
plt.figure(figsize=(12, 6))
sns.set_style("whitegrid")
sns.set_palette("pastel")
ax = sns.barplot(x=min_android_df.index, y='Counts', data=min_android_df)
plt.title('Most Common Minimum Android Versions')
plt.xlabel('Minimum Android Version')
plt.ylabel('Frequency')
plt.xticks(rotation=45)
plt.show()
```



Relationship between Ratings and Installs

In [45]:

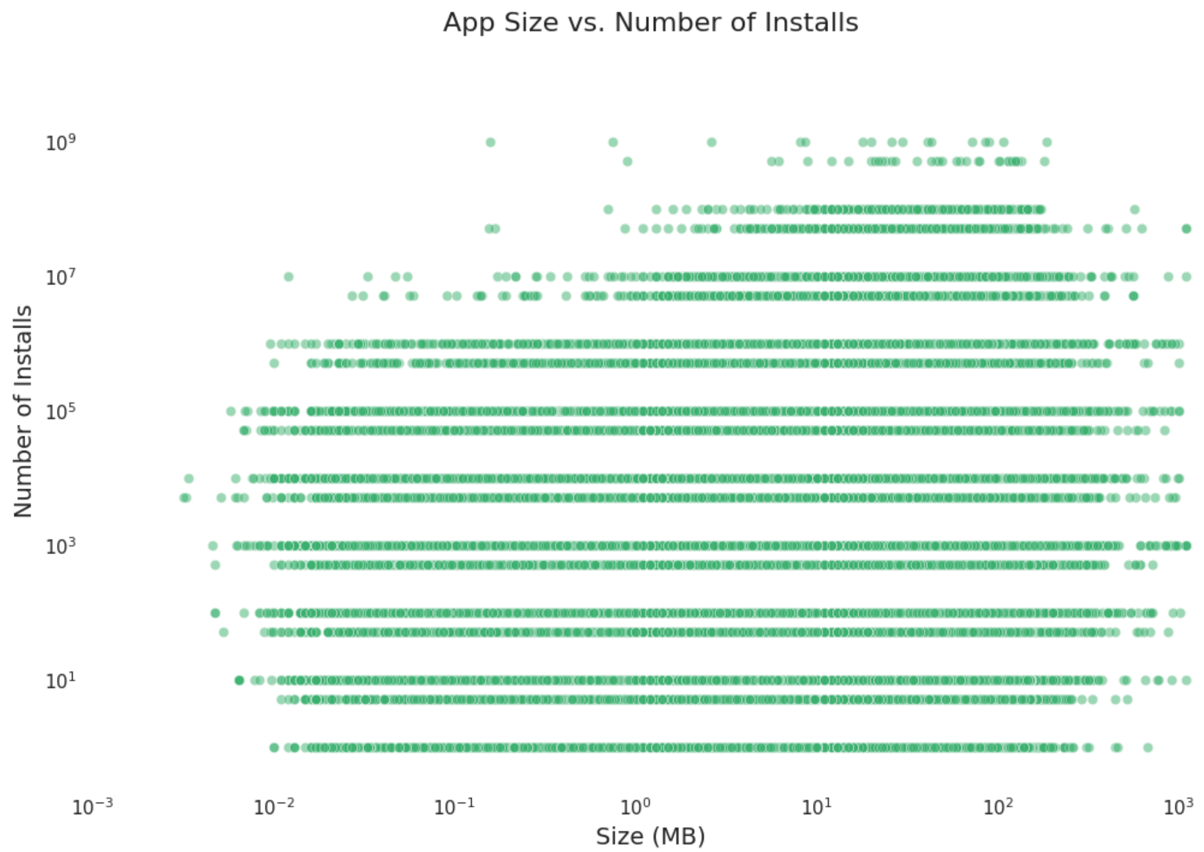
```
df['Installs_numeric'] = df['Minimum Installs'].apply(lambda x: int(x) if x
plt.figure(figsize=(10, 5))
sns.scatterplot(x='Installs_numeric', y='Rating', data=df, alpha=0.5)
plt.xscale('log')
plt.title('Relationship between Ratings and Installs')
plt.xlabel('Minimum Installs (log scale)')
plt.ylabel('Rating')
plt.show()
```



Is there a relationship between app size and the number of installs?

In [46]:

```
# Filter out rows with missing Size_MB or Installs_clean
filtered_data = df.dropna(subset=['Size', 'Installs_clean'])

# Set the color palette and minimal style
sns.set(style="white", palette="pastel")

# Create the plot
plt.figure(figsize=(12, 8))
sns.scatterplot(data=filtered_data, x="Size", y="Installs_clean", alpha=0.5,

# Customize the plot
plt.title('App Size vs. Number of Installs', fontsize=16)
plt.xlabel('Size (MB)', fontsize=14)
plt.ylabel('Number of Installs', fontsize=14)
plt.xscale("log")
plt.yscale("log")
plt.xlim(0.001, filtered_data["Size"].max())

# Remove unnecessary plot elements
sns.despine(left=True, bottom=True)

# Show the plot
plt.show()
```



Data Modelling

In [47]:
```
# Importing Modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import StandardScaler, OneHotEncoder
```

LinearRegression

In [48]:
```
data=df.copy()
```

In [49]:
```
# Clean up the 'Installs' column
data['Installs_clean'] = data['Installs'].str.replace('[^0-9]', '', regex=Tr
```

In [50]:
```
# Import necessary libraries
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import LinearRegression

# Select features and preprocess the dataset
selected_features = ['Category', 'Size', 'Installs_clean', 'Free', 'Price',
data_sample = data.sample(frac=0.1, random_state=42)
```

```python
data_filtered = data_sample.dropna(subset=selected_features + ['Rating']).cc

# One-hot encode categorical features
categorical_features = ['Category', 'Content Rating']
numerical_features = ['Size', 'Installs_clean', 'Price']

# Split the data into training and testing sets
X = data_filtered[selected_features]
y = data_filtered['Rating']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar
```

In [51]:

```python
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_features),
        ('cat', OneHotEncoder(), categorical_features)
    ])
# Create a pipeline with preprocessing and the Linear Regression model
model_lr = Pipeline([
    ('preprocessor', preprocessor),
    ('linear_regression', LinearRegression())
])
```

In [52]:

```python
# Train the Linear Regression model
model_lr.fit(X_train, y_train)

# Make predictions and evaluate the model
y_pred_lr = model_lr.predict(X_test)
mse_lr = mean_squared_error(y_test, y_pred_lr)
r2_lr = r2_score(y_test, y_pred_lr)

print(f"Linear Regression - MSE: {mse_lr:.2f}, R2: {r2_lr:.2f}")
```

```
Linear Regression - MSE: 4.25, R2: 0.04
```

K-Nearest Neighbors

In [53]:

```python
from sklearn.neighbors import KNeighborsRegressor

preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_features),
        ('cat', OneHotEncoder(), categorical_features)
    ])

# Create a pipeline with preprocessing and the KNeighborsRegressor model
model_knn = Pipeline([
    ('preprocessor', preprocessor),
    ('kneighbors', KNeighborsRegressor(n_neighbors=5))
])
```

In [54]:

```python
# Train the KNeighborsRegressor model
model_knn.fit(X_train, y_train)

# Make predictions and evaluate the model
```

```
y_pred_knn = model_knn.predict(X_test)
mse_knn = mean_squared_error(y_test, y_pred_knn)
r2_knn = r2_score(y_test, y_pred_knn)
print(f'K-Nearest Neighbors - MSE: {mse_knn:.2f}, R2: {r2_knn:.2f}')
```

```
K-Nearest Neighbors - MSE: 3.10, R2: 0.30
```

DecisionTreeRegressor

In [55]:

```
from sklearn.tree import DecisionTreeRegressor
from sklearn.inspection import permutation_importance

data_sample = data.sample(frac=0.1, random_state=42)

selected_features = ['Category', 'Rating Count', 'Size', 'Installs_clean', '
data_filtered = data_sample.dropna(subset=selected_features + ['Rating']).cc

# One-hot encode categorical features
categorical_features = ['Category', 'Content Rating']
data_features_encoded = pd.get_dummies(data_filtered[selected_features], col

# Split the dataset into training and testing sets
X = data_features_encoded
y = data_filtered['Rating']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1, rar
```

In [57]:

```
# Create and train the DecisionTree model
model_dtr = DecisionTreeRegressor(random_state=42)
model_dtr.fit(X_train, y_train)

# Make predictions and evaluate the model
y_pred_dtr = model_dtr.predict(X_test)
mse_dtr = mean_squared_error(y_test, y_pred_dtr)
r2_dtr = r2_score(y_test, y_pred_dtr)
print(f"DecisionTreeRegressor - MSE: {mse_dtr:.2f}, R2: {r2_dtr:.2f}")
```

```
DecisionTreeRegressor - MSE: 0.41, R2: 0.91
```

RandomForest model

In [58]:

```
from sklearn.ensemble import RandomForestRegressor
```

In [59]:

```
# Create and train the RandomForest model
model_rf = RandomForestRegressor(n_estimators=10, random_state=42)
model_rf.fit(X_train, y_train)

# Make predictions and evaluate the model
y_pred_rf = model_rf.predict(X_test)
mse_rf = mean_squared_error(y_test, y_pred_rf)
r2_rf = r2_score(y_test, y_pred_rf)
print(f"Random Forest - MSE: {mse_rf:.2f}, R2: {r2_rf:.2f}")
```

```
Random Forest - MSE: 0.26, R2: 0.94
```

Predicting the App rating

In [60]:
```
new=X_test.iloc[1:2,:]
```

In [61]:
```
 model_rf.predict(new)
```

Out[61]:
```
array([4.33])
```

In [63]:
```
y_test[1:2]
```

Out[63]:
```
2239666    4.2
Name: Rating, dtype: float64
```