```
from google.colab import files
# upload the file
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

Saving Customer Data.csv to Customer Data.csv

import pandas as pd

df = pd.read_csv("Customer Data.csv")

#view first 5 lines
df.head()

_ →		Customer_ID	Name	Email	Phone_Number	Address	Country	City	Postal_Code	Date_of_Birth	Sig
	0	260bdf8c- 00d3-4f67- b409- 2c5cee3d64cb	Nicole Ramos	lopezmorgan@cowan.com	941-554-3132	660 Gray Rapid, Annechester, HI 34762	Pakistan	Nelsonberg	72381	1/06/1983	
	1	9519979b- 1d76-4724- b0ef- 444c370f0236	Kayla Miranda	bcasey@stewart.info	001-112-289- 1767x88007	539 Hill Cliffs, Port Maryville, SC 51806	French Polynesia	South Charles	2039	5/02/2005	2
	2	7d58930f- 326f-47e8- 9fd7- be87631e41d6	Paula Goodman	ortizcassandra@becker- lewis.net	(977)253-6780	9094 Amanda Pass, West Crystalstad, MN 40344	Puerto Rico	New Kayla	5141	25/04/1981	1
	3	7e4897d4- ee3a-4462- 92e5- 9deb6d505ae2	Brandon Fisher	qbolton@yahoo.com	(395)637- 7172x12097	Unit 5283 Box 8114, DPO AE 02718	Mauritius	South Josephhaven	91393	17/04/2006	
	4	a1c82dfb- f3d5-4eae- bb34- b4d50a7b6c73	Christopher Hopkins	dianebanks@hotmail.com	053-523- 9452x05828	6872 Mcdonald Corners Apt. 417, Kleinton, VA 9	Cote d'Ivoire	North Jonathan	32299	17/03/1968	1
	4										•

Check data types
df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29965 entries, 0 to 29964
Data columns (total 17 columns):
                   Non-Null Count Dtype
 # Column
---
                   10000 non-null object
 0
    Customer_ID
 1
    Name
                   29965 non-null object
    Email
                   29965 non-null object
 3
    Phone_Number
                   29965 non-null
                                  object
 4
    Address
                   29965 non-null
                                  object
    Country
                   29965 non-null object
                   29965 non-null
    City
                                  object
    Postal_Code
                   29965 non-null int64
    Date_of_Birth 29965 non-null object
 8
    Signup_Date
                   29965 non-null object
                    29965 non-null
 10
    Gender
                                  object
 11 Order_Date
                   29965 non-null object
                   29965 non-null
 12 Product_Name
                                  object
 13 Quantity
                   29965 non-null int64
 14 Unit_Price
                   29965 non-null int64
 15 Total_Amount
                   29965 non-null int64
 16 Payment_Method 29965 non-null object
dtypes: int64(4), object(13)
memory usage: 3.9+ MB
```

```
# Converting date columns to datetime format
df["Date_of_Birth"] = pd.to_datetime(df["Date_of_Birth"], format="%d/%m/%Y", errors="coerce")
df["Signup_Date"] = pd.to_datetime(df["Signup_Date"], format="%d/%m/%Y", errors="coerce")
df["Order_Date"] = pd.to_datetime(df["Order_Date"], format="%d/%m/%Y", errors="coerce")
```

For check

df.info()

```
<class 'pandas.core.frame.DataFrame'>
    RangeIndex: 29965 entries, 0 to 29964
    Data columns (total 17 columns):
        Column
                       Non-Null Count Dtype
         Customer_ID
                        10000 non-null object
     1
        Name
                        29965 non-null
                                       object
                        29965 non-null object
         Email
         Phone_Number
                        29965 non-null
                                       object
        Address
                        29965 non-null
                                       object
                        29965 non-null
        Country
                                       object
        City
                        29965 non-null
                                       object
        Postal_Code
                        29965 non-null int64
        Date_of_Birth
                        29965 non-null datetime64[ns]
        Signup_Date
                        29965 non-null datetime64[ns]
     10
        Gender
                        29965 non-null
                                       object
        Order_Date
                        29965 non-null datetime64[ns]
     11
        Product Name
                        29965 non-null
     12
                                       obiect
                        29965 non-null int64
     13
        Quantity
                        29965 non-null int64
     14 Unit_Price
                        29965 non-null int64
     15 Total_Amount
     16 Payment_Method 29965 non-null object
    dtypes: datetime64[ns](3), int64(4), object(10)
    memory usage: 3.9+ MB
```

Start coding or generate with AI.

Check number of missing data
df.isnull().sum()



df[df["Customer_ID"].isnull()].head(20)

₹

	Customer_ID	Name	Email	Phone_Number	Address	Country	City	Postal_Code	Date_of_Birth	Signup_Date	Gender	Or
10000	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10001	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10002	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10003	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10004	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10005	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10006	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10007	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10008	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10009	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10010	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10011	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10012	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10013	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10014	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10015	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10016	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10017	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10018	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
10019	NaN	Unknown	Unknown	Unknown	Unknown	Unknown	Unknown	0	2025-02-09	2025-02-09	Other	2
4												•
	10001 10002 10003 10004 10005 10006 10007 10008 10009 10010 10011 10012 10013 10014 10015 10016 10017 10018 10019	10000 NaN 10001 NaN 10002 NaN 10003 NaN 10004 NaN 10005 NaN 10006 NaN 10007 NaN 10008 NaN 10009 NaN 10010 NaN 10011 NaN 10012 NaN 10012 NaN 10013 NaN 10014 NaN 10015 NaN 10015 NaN 10016 NaN 10017 NaN 10017 NaN	10000 NaN Unknown 10001 NaN Unknown 10002 NaN Unknown 10003 NaN Unknown 10004 NaN Unknown 10005 NaN Unknown 10006 NaN Unknown 10007 NaN Unknown 10008 NaN Unknown 10009 NaN Unknown 10010 NaN Unknown 10011 NaN Unknown 10012 NaN Unknown 10012 NaN Unknown 10013 NaN Unknown 10014 NaN Unknown 10015 NaN Unknown 10016 NaN Unknown 10016 NaN Unknown 10017 NaN Unknown 10017 NaN Unknown 10018 NaN Unknown 10018 NaN Unknown 10019 NaN Unknown	10000 NaN Unknown Unknown 10001 NaN Unknown Unknown 10002 NaN Unknown Unknown 10003 NaN Unknown Unknown 10004 NaN Unknown Unknown 10005 NaN Unknown Unknown 10006 NaN Unknown Unknown 10007 NaN Unknown Unknown 10008 NaN Unknown Unknown 10010 NaN Unknown Unknown 10011 NaN Unknown Unknown 10012 NaN Unknown Unknown 10013 NaN Unknown Unknown 10014 NaN Unknown Unknown 10015 NaN Unknown Unknown 10016 NaN Unknown Unknown 10017 NaN Unknown Unknown 10018 NaN Unknown Unknown	10000 NaN Unknown Unknown Unknown 10001 NaN Unknown Unknown Unknown 10002 NaN Unknown Unknown Unknown 10003 NaN Unknown Unknown Unknown 10004 NaN Unknown Unknown Unknown 10005 NaN Unknown Unknown Unknown 10006 NaN Unknown Unknown Unknown 10007 NaN Unknown Unknown Unknown 10008 NaN Unknown Unknown Unknown 10019 NaN Unknown Unknown Unknown 10010 NaN Unknown Unknown Unknown 10011 NaN Unknown Unknown Unknown 10012 NaN Unknown Unknown Unknown 10013 NaN Unknown Unknown Unknown 10014 NaN Unknown Unknown <	10000 NaN Unknown Unknown Unknown Unknown 10001 NaN Unknown Unknown Unknown Unknown 10002 NaN Unknown Unknown Unknown Unknown 10003 NaN Unknown Unknown Unknown Unknown 10004 NaN Unknown Unknown Unknown Unknown 10005 NaN Unknown Unknown Unknown Unknown 10006 NaN Unknown Unknown Unknown Unknown 10007 NaN Unknown Unknown Unknown Unknown 10008 NaN Unknown Unknown Unknown Unknown 10010 NaN Unknown Unknown Unknown Unknown 10011 NaN Unknown Unknown Unknown Unknown 10012 NaN Unknown Unknown Unknown Unknown 10013 NaN Unknown <t< th=""><th>10000 NaN Unknown Unknown Unknown Unknown Unknown 10001 NaN Unknown Unknown Unknown Unknown Unknown Unknown 10002 NaN Unknown Unknown Unknown Unknown Unknown Unknown 10003 NaN Unknown Unknown</th><th>10000 NaN Unknown Unkn</th><th>10000 NaN Unknown Unkn</th><th>10000 NaN Unknown Unkn</th><th>10000 NaN Unknown Unknown Unknown Unknown Unknown Unknown Unknown Unknown Unknown 0 2025-02-09 2025-02-09 10001 NaN Unknown Unknown Unknown Unknown Unknown Unknown Unknown 0 2025-02-09 2025-02-09 10002 NaN Unknown Unknown Unknown Unknown Unknown Unknown Unknown 0 2025-02-09 2025-02-09 10004 NaN Unknown Unknown Unknown Unknown Unknown Unknown Unknown Onknown O 2025-02-09 2025-02-09 10005 NaN Unknown Unknown Unknown Unknown Unknown Unknown Unknown O 2025-02-09 2025-02-09 10006 NaN Unknown Unknown Unknown Unknown Unknown Unknown Unknown O 2025-02-09 2025-02-09 10007 NaN Unknown U</th><th>10000 NaN Unknown Unkn</th></t<>	10000 NaN Unknown Unknown Unknown Unknown Unknown 10001 NaN Unknown Unknown Unknown Unknown Unknown Unknown 10002 NaN Unknown Unknown Unknown Unknown Unknown Unknown 10003 NaN Unknown Unknown	10000 NaN Unknown Unkn	10000 NaN Unknown Unkn	10000 NaN Unknown Unkn	10000 NaN Unknown Unknown Unknown Unknown Unknown Unknown Unknown Unknown Unknown 0 2025-02-09 2025-02-09 10001 NaN Unknown Unknown Unknown Unknown Unknown Unknown Unknown 0 2025-02-09 2025-02-09 10002 NaN Unknown Unknown Unknown Unknown Unknown Unknown Unknown 0 2025-02-09 2025-02-09 10004 NaN Unknown Unknown Unknown Unknown Unknown Unknown Unknown Onknown O 2025-02-09 2025-02-09 10005 NaN Unknown Unknown Unknown Unknown Unknown Unknown Unknown O 2025-02-09 2025-02-09 10006 NaN Unknown Unknown Unknown Unknown Unknown Unknown Unknown O 2025-02-09 2025-02-09 10007 NaN Unknown U	10000 NaN Unknown Unkn

Delete rows with missing Customer_ID df = df.dropna(subset=["Customer ID"])

```
df.info()
   <class 'pandas.core.frame.DataFrame'>
    Index: 10000 entries, 0 to 9999
    Data columns (total 17 columns):
                        Non-Null Count Dtype
     # Column
                        10000 non-null object
     0
         Customer_ID
     1
         Name
                        10000 non-null
                                        object
         Email
                        10000 non-null object
         Phone_Number
                        10000 non-null
                                        object
         Address
                        10000 non-null
                                        object
         Country
                        10000 non-null
                                        object
                        10000 non-null object
         City
         Postal_Code
                         10000 non-null int64
         Date_of_Birth 10000 non-null datetime64[ns]
         Signup_Date
                        10000 non-null
                                        datetime64[ns]
     10 Gender
                        10000 non-null object
     11 Order_Date
                        10000 non-null datetime64[ns]
     12 Product_Name
                        10000 non-null object
     13 Quantity
                        10000 non-null
                                        int64
     14 Unit_Price
                         10000 non-null
                                        int64
     15 Total_Amount
                        10000 non-null int64
     16 Payment_Method 10000 non-null object
    dtypes: datetime64[ns](3), int64(4), object(10)
    memory usage: 1.4+ MB
# Save the cleaned dataset as a new CSV file
df.to_csv("cleaned_customer_data.csv", index=False)
import os
os.listdir()
['.config', 'Customer Data.csv', 'cleaned_customer_data.csv', 'sample_data']
from google.colab import files
# Download the cleaned CSV file
```

files.download("cleaned_customer_data.csv")



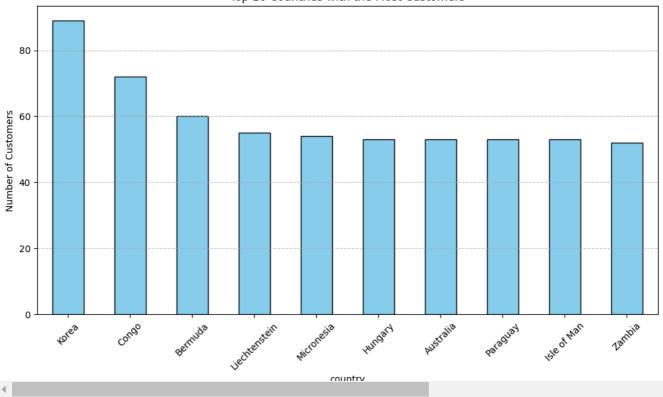
```
import matplotlib.pyplot as plt

# By number of customers by country
country_counts = df["Country"].value_counts().head(10)  # İlk 10 ülke

# visualize
plt.figure(figsize=(12,6))
country_counts.plot(kind="bar", color="skyblue", edgecolor="black")
plt.title("Top 10 Countries with the Most Customers")
plt.xlabel("country")
plt.ylabel("Number of Customers")
plt.xticks(rotation=45)
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
```



Top 10 Countries with the Most Customers



In customer analysis, marketing efforts may be more effective in countries such as Korea and Congo.

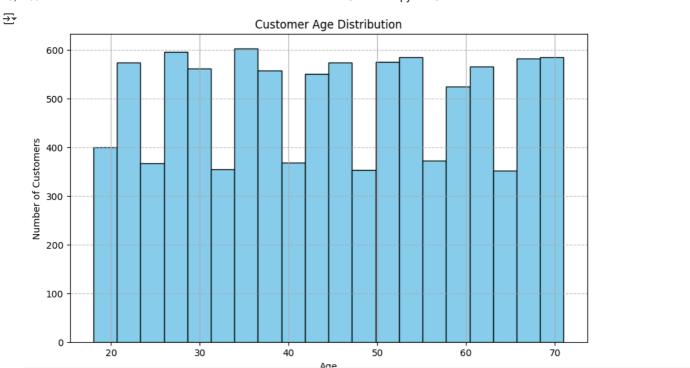
There may be more sales in these countries because the customer base is larger.

```
from datetime import datetime

# Get today's date
today = datetime.today()

#Calculate age (Today - Date of Birth)
df["Age"] = today.year - df["Date_of_Birth"].dt.year

#Visualizing age distribution
plt.figure(figsize=(10,6))
df["Age"].hist(bins=20, color="skyblue", edgecolor="black")
plt.title("Customer Age Distribution")
plt.xlabel("Age")
plt.ylabel("Age")
plt.ylabel("Number of Customers")
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
```



The largest number of customers are between the ages of 25-30 and 55-60! There are almost no customers under the age of 18. The age distribution is generally balanced, but there are clear peaks in some age groups. What does this mean?

If a marketing strategy is to be created, the 25-30 age range can be focused on. Customers in the middle age group (55-60 years old) may also be an important target. The young age group (18-20 years old) customer base is low, perhaps special campaigns can be organized for this audience.

```
import matplotlib.pyplot as plt

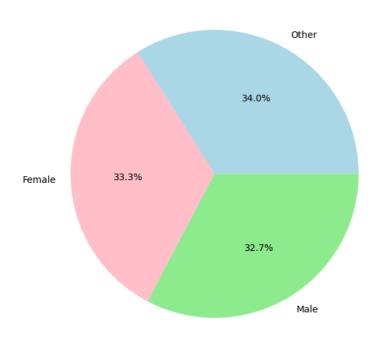
# Count the number of customers by gender
gender_counts = df["Gender"].value_counts()

# Create a pie chart
plt.figure(figsize=(7,7))
plt.pie(gender_counts, labels=gender_counts.index, autopct="%1.1f%%", colors=["lightblue", "pink", "lightgreen"])
plt.title("Customer Gender Distribution")
plt.show()
```



4

Customer Gender Distribution



"Other" category has the highest percentage (34.0%) Female customers make up 33.3% Male customers account for 32.7% What does this man?

The gender distribution is fairly balanced, with no single group dominating the customer base. Marketing campaigns should be designed inclusively since all gender categories have a significant presence. If needed, further investigation could reveal whether certain product categories are more popular among specific gender groups.

```
import seaborn as sns

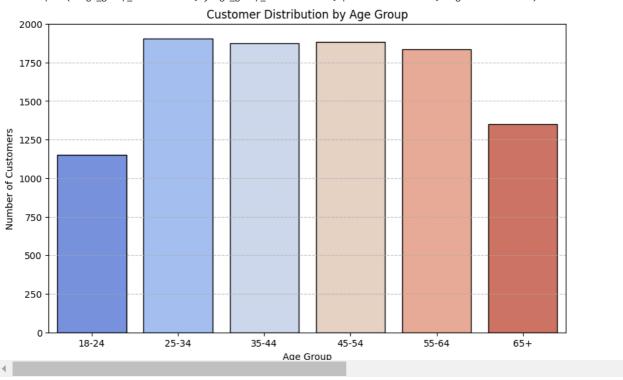
# Define age groups
age_bins = [18, 25, 35, 45, 55, 65, 75]
age_labels = ["18-24", "25-34", "35-44", "45-54", "55-64", "65+"]
df["Age_Group"] = pd.cut(df["Age"], bins=age_bins, labels=age_labels, right=False)

# Count customers in each age group
age_group_counts = df["Age_Group"].value_counts().sort_index()

# Visualize the age group distribution
plt.figure(figsize=(10,6))
sns.barplot(x=age_group_counts.index, y=age_group_counts.values, palette="coolwarm", edgecolor="black")
plt.title("Customer Distribution by Age Group")
plt.ylabel("Number of Customers")
plt.ylabel("Number of Customers")
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
```

<ipython-input-14-0bc05037ae35>:13: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `le sns.barplot(x=age_group_counts.index, y=age_group_counts.values, palette="coolwarm", edgecolor="black")

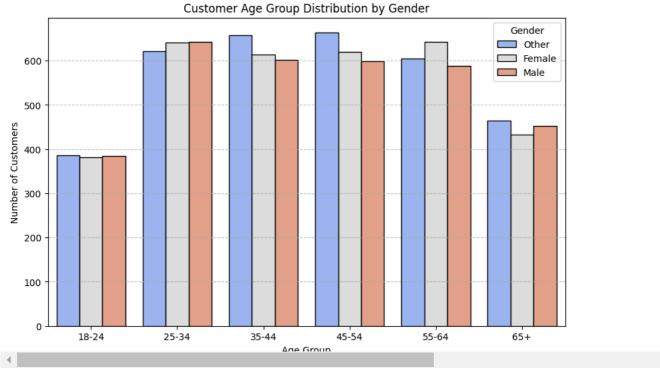


Age Group Insights The 25-34 age group has the highest number of customers. 35-44, 45-54, and 55-64 age groups have a similar number of customers. The 18-24 and 65+ age groups have fewer customers compared to others.

The 25-34 age group is the most active customer segment. This group should be a focus for marketing efforts. The 65+ and 18-24 groups are underrepresented. If the company wants to expand its reach, it may need different marketing strategies to attract these groups.

```
plt.figure(figsize=(10,6))
sns.countplot(x="Age_Group", hue="Gender", data=df, palette="coolwarm", edgecolor="black")
plt.title("Customer Age Group Distribution by Gender")
plt.xlabel("Age Group")
plt.ylabel("Number of Customers")
plt.legend(title="Gender")
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
```





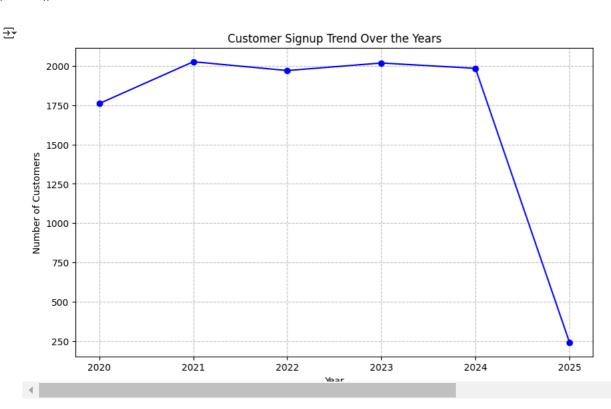
The 25-34 and 45-54 age groups are the most active customer base, so these segments can be targeted primarily. Special promotions or more accessible services may be offered to increase the 65+ age group.

```
import matplotlib.pyplot as plt

# Extract the year from the signup date
df["Signup_Year"] = df["Signup_Date"].dt.year

# Count the number of customers per year
signup_counts = df["Signup_Year"].value_counts().sort_index()

# Plot the customer signup trend
plt.figure(figsize=(10,6))
plt.plot(signup_counts.index, signup_counts.values, marker="o", linestyle="-", color="blue")
plt.title("Customer Signup Trend Over the Years")
plt.xlabel("Year")
plt.ylabel("Number of Customers")
plt.grid(True, linestyle="--", alpha=0.7)
plt.show()
```



Customer sign-ups in 2025 have dropped significantly compared to previous years. If the 2025 data is incomplete, this drop might be due to missing records. The company may need to review its customer acquisition strategies.

```
import numpy as np

# Define new and old customers based on signup year

df["Customer_Type"] = np.where(df["Signup_Year"] >= 2024, "New", "Old")

# Count new and old customers

customer_type_counts = df["Customer_Type"].value_counts()

# Visualize the distribution

plt.figure(figsize=(7,7))

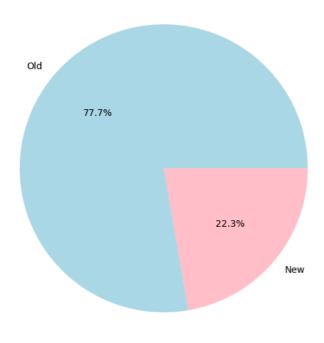
plt.pie(customer_type_counts, labels=customer_type_counts.index, autopct="%1.1f%%", colors=["lightblue", "pink"])

plt.title("New vs. Old Customers Distribution")

plt.show()
```



New vs. Old Customers Distribution



The customer base relies heavily on old customers. New customer acquisition is at a low level. The company may need more aggressive marketing strategies to attract new customers.

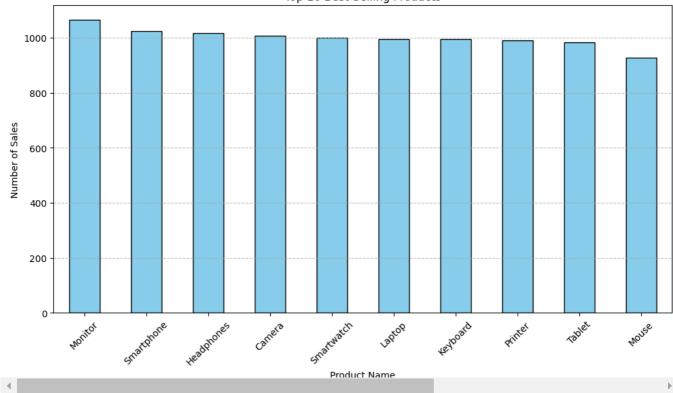
```
import matplotlib.pyplot as plt

# Count the number of sales per product
top_products = df["Product_Name"].value_counts().head(10)  # Top 10 products

# Visualize the data
plt.figure(figsize=(12,6))
top_products.plot(kind="bar", color="skyblue", edgecolor="black")
plt.title("Top 10 Best-Selling Products")
plt.xlabel("Product Name")
plt.ylabel("Number of Sales")
plt.xticks(rotation=45)
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
```

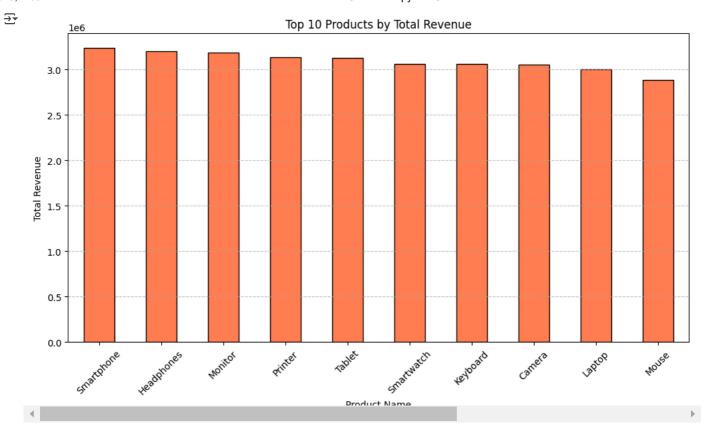
₹

Top 10 Best-Selling Products



Monitor is the best-selling product. Smartphone, Headphones, Camera, and Smartwatch have high sales. Sales volume is very close among the top 10 products. Stock management is crucial for monitors and other top-selling products. The reasons for low sales of other products should be analyzed.

```
# Calculate total revenue per product
product_revenue = df.groupby("Product_Name")["Total_Amount"].sum().sort_values(ascending=False).head(10)
# Visualize revenue distribution
plt.figure(figsize=(12,6))
product_revenue.plot(kind="bar", color="coral", edgecolor="black")
plt.title("Top 10 Products by Total Revenue")
plt.xlabel("Product Name")
plt.ylabel("Total Revenue")
plt.xticks(rotation=45)
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
```



Smartphone is the highest revenue-generating product. Headphones, Monitor, and Printer are also among the top revenue-generating products. Revenue is evenly distributed among the top 10 products. Stock management and promotions are crucial for these products.

```
# Find the average price of least-selling products
least_selling_avg_price = df.groupby("Product_Name")["Unit_Price"].mean().sort_values().head(10)

# Visualize the price distribution
plt.figure(figsize=(12,6))
least_selling_avg_price.plot(kind="bar", color="purple", edgecolor="black")
plt.title("Average Price of Least-Selling Products")
plt.xlabel("Product Name")
plt.ylabel("Average Unit Price")
plt.xticks(rotation=45)
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
```

1000

800

600

400

200

0

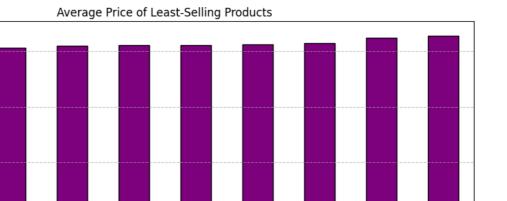
Camera

Average Unit Price

keyboard

Product Name





Smattwatch

Tablet

printer

Low-selling products are generally high-priced. More affordable alternatives could be offered for price-sensitive customers. Installment payment options could improve accessibility.

Mouse

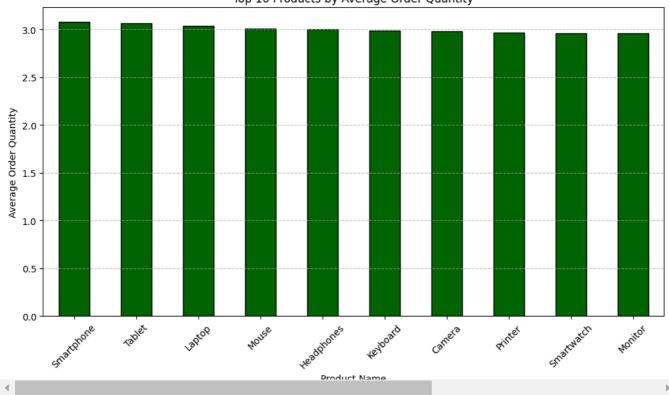
Smartphone

```
# Calculate the average order quantity per product
avg_order_quantity = df.groupby("Product_Name")["Quantity"].mean().sort_values(ascending=False)

# Visualize the data
plt.figure(figsize=(12,6))
avg_order_quantity.head(10).plot(kind="bar", color="darkgreen", edgecolor="black")
plt.title("Top 10 Products by Average Order Quantity")
plt.xlabel("Product Name")
plt.ylabel("Average Order Quantity")
plt.xticks(rotation=45)
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
```

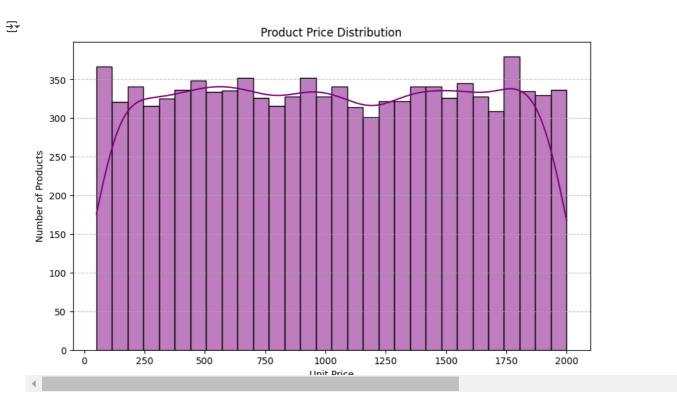






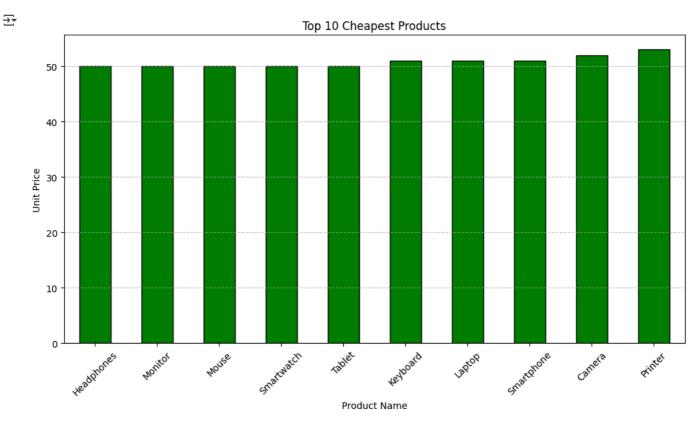
Smartphone, Tablet, and Laptop have the highest average order quantities. Mouse, Headphones, and Keyboard also have high order quantities. This suggests a bulk purchase trend for certain products.

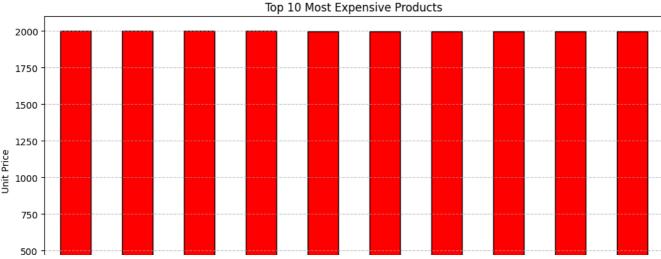
```
# Visualize the distribution of product prices
plt.figure(figsize=(10,6))
sns.histplot(df["Unit_Price"], bins=30, kde=True, color="purple", edgecolor="black")
plt.title("Product Price Distribution")
plt.xlabel("Unit Price")
plt.ylabel("Number of Products")
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
```



Product prices are spread over a wide range. The price distribution seems relatively balanced.

```
# Identify the cheapest and most expensive products
cheapest_products = df.groupby("Product_Name")["Unit_Price"].min().sort_values().head(10)
most\_expensive\_products = df.groupby("Product\_Name")["Unit\_Price"].max().sort\_values(ascending=False).head(10) \\
# Visualize the cheapest products
plt.figure(figsize=(12,6))
cheapest_products.plot(kind="bar", color="green", edgecolor="black")
plt.title("Top 10 Cheapest Products")
plt.xlabel("Product Name")
plt.ylabel("Unit Price")
plt.xticks(rotation=45)
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
# Visualize the most expensive products
plt.figure(figsize=(12,6))
most_expensive_products.plot(kind="bar", color="red", edgecolor="black")
plt.title("Top 10 Most Expensive Products")
plt.xlabel("Product Name")
plt.ylabel("Unit Price")
plt.xticks(rotation=45)
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.show()
```





The cheapest products are usually low-cost and commonly used items. The most expensive products are technology-based (e.g., laptops, cameras, smartwatches). Cheap products have higher sales potential due to low prices, while expensive products provide higher profit margins.

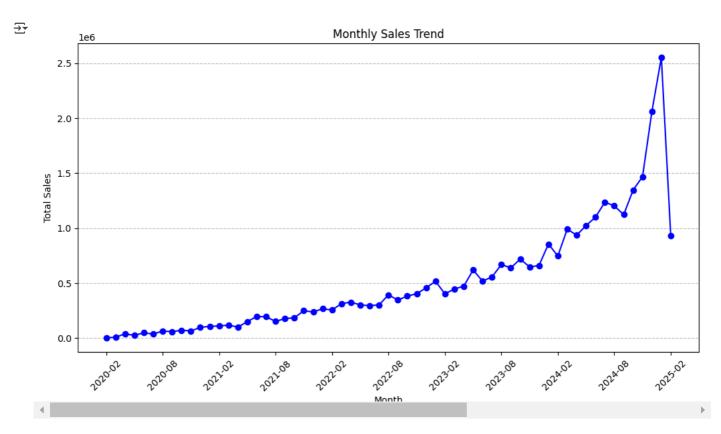
```
#Convert Order_Date column to date format. Thus, let's find the total sales amount made each month.
df['Order_Date'] = pd.to_datetime(df['Order_Date'])
monthly_sales = df.groupby(df['Order_Date'].dt.to_period("M"))['Total_Amount'].sum()
monthly_sales.index = monthly_sales.index.astype(str)
```

```
plt.figure(figsize=(12,6)) # Set figure size
plt.plot(monthly_sales.index, monthly_sales.values, marker='o', linestyle='-', color='b') # Line chart

plt.xlabel("Month") # X-axis label
plt.ylabel("Total Sales") # Y-axis label
plt.title("Monthly Sales Trend") # Chart title

plt.xticks(range(0, len(monthly_sales), 6), monthly_sales.index[::6], rotation=45) # Reduce x-axis labels
plt.grid(axis="y", linestyle="--", alpha=0.7) # Add grid lines on y-axis

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

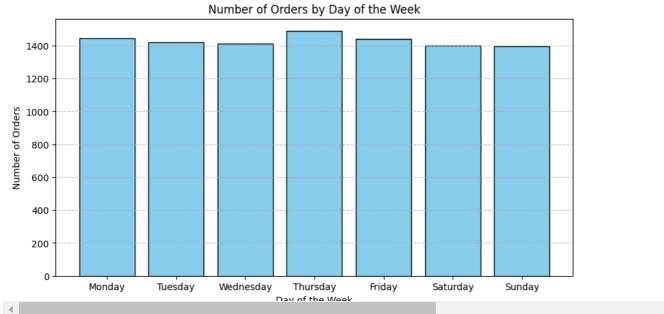


Steady growth trend since 2020 Sharp increase from mid-2024 Sudden drop at the beginning of 2025 There might have been a discount period or a seasonal shopping boom at the end of 2024. The drop in 2025 could be due to missing or incorrect data. (New competitors or economic changes might have caused a sudden drop in sales.

```
import matplotlib.pyplot as plt
import pandas as pd
# Convert 'Order_Date' to datetime format
df["Order_Date"] = pd.to_datetime(df["Order_Date"])
# Extract day of the week and count the number of orders
df["Day_of_Week"] = df["Order_Date"].dt.day_name()
order_counts = df["Day_of_Week"].value_counts()
# Sort the days to follow the correct weekly order
order_counts = order_counts.reindex(
    ["Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday", "Sunday"]
# Plot the data
plt.figure(figsize=(10,5))
plt.bar(order_counts.index, order_counts.values, color="skyblue", edgecolor="black")
plt.xlabel("Day of the Week")
plt.ylabel("Number of Orders")
\verb|plt.title("Number of Orders by Day of the Week")|\\
plt.grid(axis="y", linestyle="--", alpha=0.7)
# Show the plot
```

plt.show()





The most orders seem to be placed on Thursday. During business days, customers may be more inclined to place orders. If there is a drop in orders on weekends, it can be useful to analyze this situation and plan special campaigns on weekends.

```
import matplotlib.pyplot as plt

# Group orders by payment method
payment_counts = df["Payment_Method"].value_counts()

# Create the plot
plt.figure(figsize=(10, 5))
plt.bar(payment_counts.index, payment_counts.values, color='blue', alpha=0.7, edgecolor='black')
plt.xlabel("Payment Method") # X-axis label
plt.ylabel("Number of Orders") # Y-axis label
```