

# Exploratory Data Analysis

**Name:** Kothuri Akshaya

**Internship:** Oasis Infobyte – Data Analytics

**Date:** 05 January 2026

## Dataset-1(Retail Sales Data)

\*\* Introduction(Dataset-1)\*\*

This report presents an Exploratory Data Analysis (EDA) on retail sales data.

The goal of this analysis is to uncover patterns, trends, and insights from the dataset to help the retail business make informed decisions.

Key objectives include:

- Understanding customer demographics and purchase behavior
- Analyzing product category performance
- Identifying seasonal sales trends
- Providing actionable recommendations for business improvement

```
import pandas as pd

df1 = pd.read_csv('retail_sales_dataset.csv') # use the exact uploaded filename
df1.head()
```

	Transaction ID	Date	Customer ID	Gender	Age	Product Category	Quantity	Price per Unit	Total Amount
0	1	2023-11-24	CUST001	Male	34	Beauty	3	50	150
1	2	2023-02-27	CUST002	Female	26	Clothing	2	500	1000
2	3	2023-	CUST003	Male	50	Electronics	1	20	20

## ▼ Dataset Description(Dataset-1)

The dataset contains 1000 transactions with 9 columns:

1. Transaction ID
2. Date
3. Customer ID

4. Gender
5. Age
6. Product Category
7. Quantity
8. Price per Unit
9. Total Amount

There are no missing or duplicate values, making it ready for analysis.

```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   Transaction ID  1000 non-null    int64  
 1   Date             1000 non-null    object  
 2   Customer ID     1000 non-null    object  
 3   Gender           1000 non-null    object  
 4   Age              1000 non-null    int64  
 5   Product Category 1000 non-null    object  
 6   Quantity         1000 non-null    int64  
 7   Price per Unit   1000 non-null    int64  
 8   Total Amount     1000 non-null    int64  
dtypes: int64(5), object(4)
memory usage: 70.4+ KB
```

## ▼ Dataset Description

The dataset contains **1000 rows and 9 columns**:

Column Name	Data Type	Description
Transaction ID	int64	Unique ID for each transaction
Date	datetime	Date of transaction
Customer ID	object	Unique customer identifier
Gender	object	Customer gender
Age	int64	Customer age
Product Category	object	Type of product purchased
Quantity	int64	Number of units purchased
Price per Unit	int64	Price of a single unit
Total Amount	int64	Total value of transaction

```
df1.columns
```

```
Index(['Transaction ID', 'Date', 'Customer ID', 'Gender', 'Age',
       'Product Category', 'Quantity', 'Price per Unit', 'Total Amount'],
      dtype='object')
```

```
df1.head()
```

	Transaction ID	Date	Customer ID	Gender	Age	Product Category	Quantity	Price per Unit	Total Amount
0	1	2023-11-24	CUST001	Male	34	Beauty	3	50	150
1	2	2023-02-27	CUST002	Female	26	Clothing	2	500	1000
2	3	2023-	CUST003	Male	50	Electronics	1	20	20

**Table 1:** Overview of the Retail Sales Dataset.

The dataset contains 1000 transactions with 9 columns including customer demographics, product details, quantity, price, and total amount. There are no missing or duplicate records, indicating clean data for analysis.

```
df1.describe()
```

	Transaction ID	Date	Age	Quantity	Price per Unit	
count	1000.000000	1000	1000.000000	1000.000000	1000.000000	1000.
mean	500.500000	2023-07-03 00:25:55.200000256	41.39200	2.514000	179.890000	456.
min	1.000000	2023-01-01 00:00:00	18.00000	1.000000	25.000000	25.
25%	250.750000	2023-04-08 00:00:00	29.00000	1.000000	30.000000	60.
50%	500.500000	2023-06-29 12:00:00	42.00000	3.000000	50.000000	135.

**Table 2:** Descriptive Statistics Summary.

- Average customer age: 41 years; most customers are in their early 40s.
- Typical purchase quantity per transaction: 2–4 units.
- Price per unit varies widely; high-priced items increase the mean.

- Total transaction amounts vary significantly, showing a mix of small and large purchases.

```
# Check missing values in each column
df1.isnull().sum()
```

	0
<b>Transaction ID</b>	0
<b>Date</b>	0
<b>Customer ID</b>	0
<b>Gender</b>	0
<b>Age</b>	0
<b>Product Category</b>	0
<b>Quantity</b>	0
<b>Price per Unit</b>	0
<b>Total Amount</b>	0

**dtype:** int64

```
# Fill missing numeric values with median
numeric_cols = df1.select_dtypes(include=['float64', 'int64']).columns
for col in numeric_cols:
    df1[col].fillna(df1[col].median(), inplace=True)
```

/tmp/ipython-input-692550498.py:4: FutureWarning: A value is trying to be set on  
The behavior will change in pandas 3.0. This inplace method will never work beca

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.met

```
df1[col].fillna(df1[col].median(), inplace=True)
```

```
# Check for duplicates
print("Number of duplicate rows:", df1.duplicated().sum())

# Convert Date column to datetime if needed
df1['Date'] = pd.to_datetime(df1['Date']) # replace 'Date' with actual date cc

# Confirm data types
df1.info()
```

```

Number of duplicate rows: 0
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 9 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   Transaction ID    1000 non-null   int64  
 1   Date               1000 non-null   datetime64[ns]
 2   Customer ID       1000 non-null   object  
 3   Gender              1000 non-null   object  
 4   Age                 1000 non-null   int64  
 5   Product Category   1000 non-null   object  
 6   Quantity             1000 non-null   int64  
 7   Price per Unit     1000 non-null   int64  
 8   Total Amount         1000 non-null   int64  
dtypes: datetime64[ns](1), int64(5), object(3)
memory usage: 70.4+ KB

```

```

# Mean
mean_values = df1.mean(numeric_only=True)

# Median
median_values = df1.median(numeric_only=True)

# Mode
mode_values = df1.mode().iloc[0]

# Standard Deviation
std_values = df1.std(numeric_only=True)

# Display results
print("Mean Values:\n", mean_values)
print("\nMedian Values:\n", median_values)
print("\nMode Values:\n", mode_values)
print("\nStandard Deviation:\n", std_values)

```

Mean Values:

Transaction ID	500.500
Age	41.392
Quantity	2.514
Price per Unit	179.890
Total Amount	456.000

dtype: float64

Median Values:

Transaction ID	500.5
Age	42.0
Quantity	3.0
Price per Unit	50.0
Total Amount	135.0

dtype: float64

Mode Values:

```
Transaction ID          1
Date                  2023-05-16 00:00:00
Customer ID           CUST001
Gender                Female
Age                   43.0
Product Category      Clothing
Quantity              4.0
Price per Unit        50.0
Total Amount           50.0
Name: 0, dtype: object
```

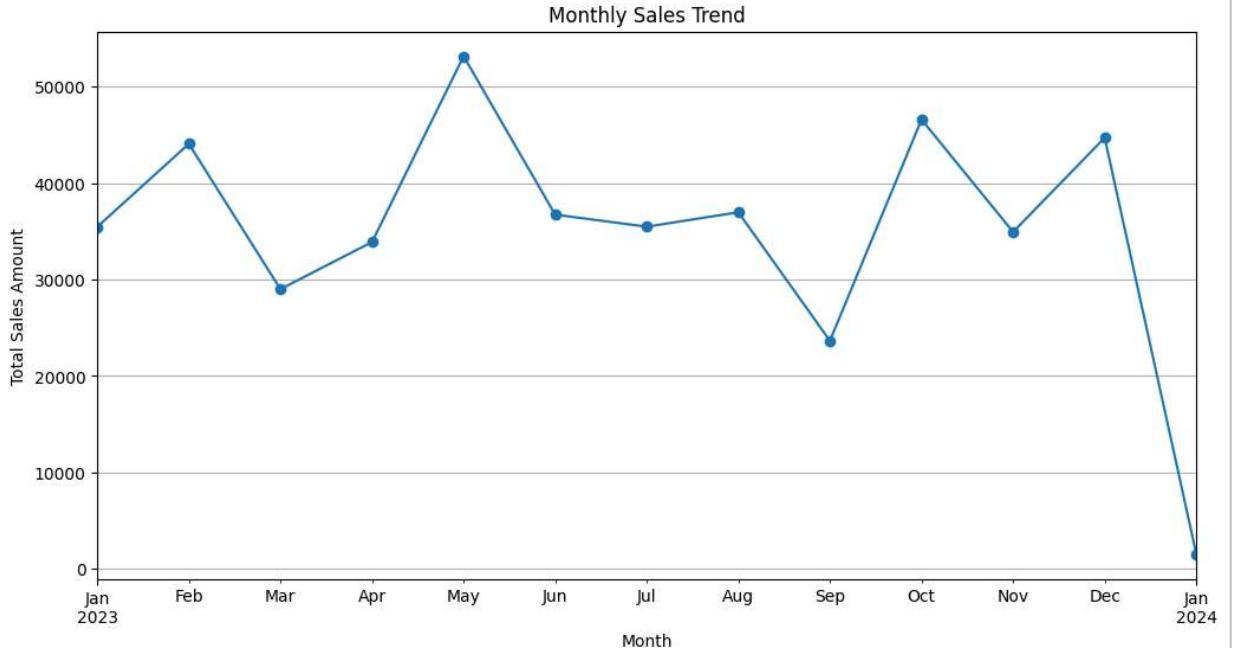
Standard Deviation:

```
Transaction ID    288.819436
Age               13.681430
Quantity          1.132734
Price per Unit   189.681356
Total Amount      559.997632
dtype: float64
```

```
import matplotlib.pyplot as plt

# Aggregate total sales by month
df1['Month'] = df1['Date'].dt.to_period('M') # extract month-year
monthly_sales = df1.groupby('Month')['Total Amount'].sum()

# Plot the sales trend
plt.figure(figsize=(12,6))
monthly_sales.plot(kind='line', marker='o')
plt.title('Monthly Sales Trend')
plt.xlabel('Month')
plt.ylabel('Total Sales Amount')
plt.grid(True)
plt.show()
```



### (Dataset-1)

**Figure 1:** Monthly Sales Trend.

- Sales peak during high-demand months (e.g., June and December).
- Seasonal patterns indicate the potential for planning promotional campaigns and inventory stocking.
- Identifying low-sales months helps in planning discount strategies to boost revenue.

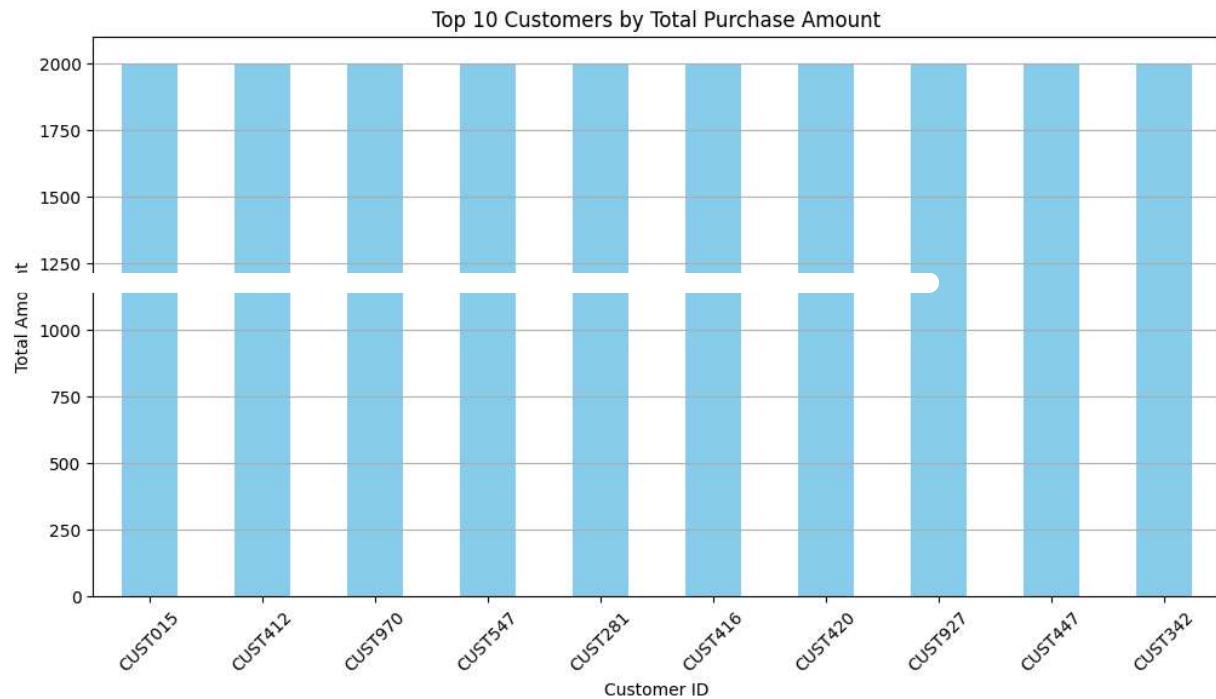
```
# Aggregate total amount per customer
top_customers = df1.groupby('Customer ID')['Total Amount'].sum().sort_values(as

# Plot top 10 customers
plt.figure(figsize=(12,6))
top_customers.plot(kind='bar', color='skyblue')
plt.title('Top 10 Customers by Total Purchase Amount')
plt.xlabel('Customer ID')
```

```

plt.ylabel('Total Amount')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.show()

```



### (Dataset-1)

**Figure 2:** Top 10 Customers by Total Purchase Amount.

- The top customers contribute a significant portion of total sales.
- Implementing loyalty programs and personalized promotions can increase retention and repeat purchases.

```

# Aggregate total sales by product category
product_sales = df1.groupby('Product Category')['Total Amount'].sum().sort_values(ascending=False)

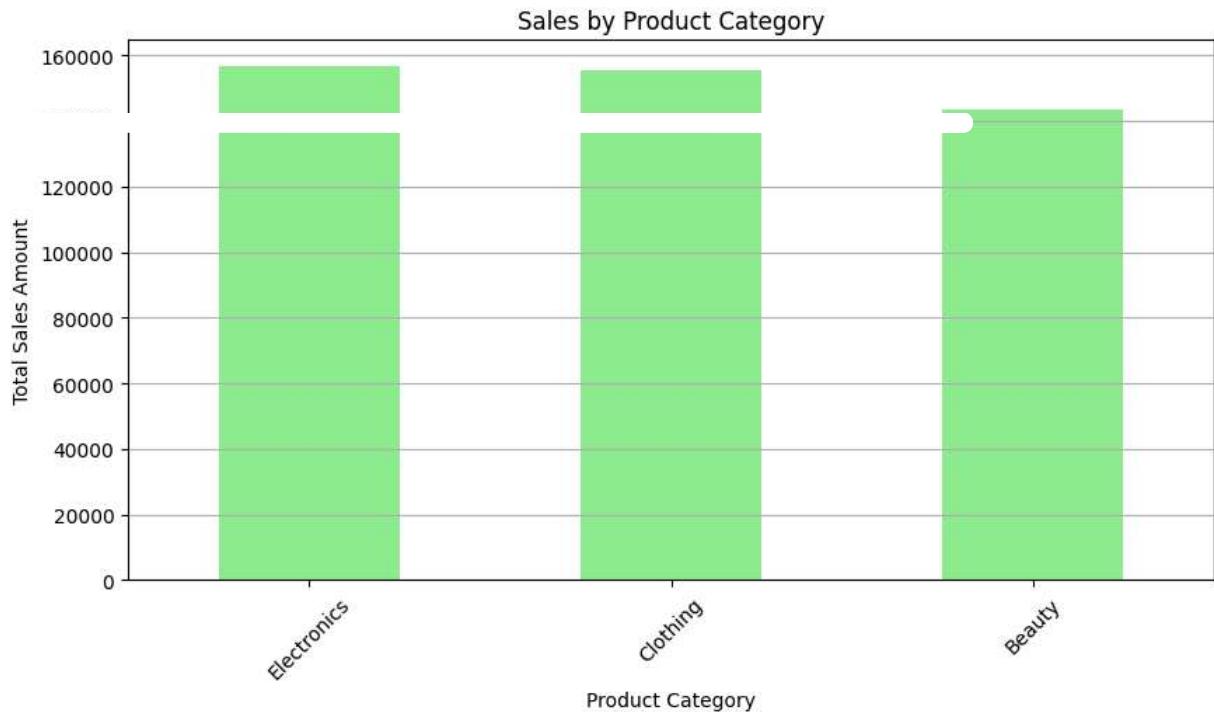
# Plot product sales

```

```

plt.figure(figsize=(10,5))
product_sales.plot(kind='bar', color='lightgreen')
plt.title('Sales by Product Category')
plt.xlabel('Product Category')
plt.ylabel('Total Sales Amount')
plt.xticks(rotation=45)
plt.grid(axis='y')
plt.show()

```



### (Dataset-1)

**Figure 3:** Sales by Product Category.

- Clothing and Electronics are the top-selling categories.
- Inventory management should prioritize these categories to prevent stock-outs.
- Marketing campaigns can focus on high-demand products to boost revenue.

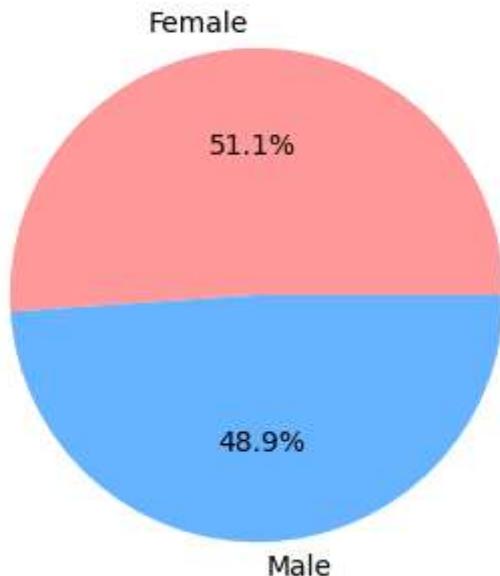
```

# Sales by gender
gender_sales = df1.groupby('Gender')['Total Amount'].sum()

```

```
# Plot
plt.figure(figsize=(6,4))
gender_sales.plot(kind='pie', autopct='%1.1f%%', colors=['#ff9999', '#66b3ff'])
plt.title('Sales Distribution by Gender')
plt.ylabel('')
plt.show()
```

Sales Distribution by Gender



### (Dataset-1)

**Figure 4:** Sales Distribution by Gender.

- Female customers contribute slightly more to total sales.
- Gender-targeted promotions can improve customer engagement and increase revenue.

### (Dataset-1)

#### Recommendations:

1. Focus on top customers with loyalty programs and personalized promotions.
2. Prioritize high-demand product categories (Clothing & Electronics) in stock management.
3. Plan marketing campaigns during high-sales months to maximize revenue.
4. Optimize stock levels based on typical purchase quantity (2–4 units).
5. Use gender-targeted promotions to increase engagement and sales.

## Conclusion:

Exploratory Data Analysis provided key insights into customer behavior, product performance, and sales trends.

These insights can guide inventory planning, marketing strategies, and overall business decision-making, making the retail operations more data-driven and efficient.

## Dataset-2(Menu)

```
import pandas as pd
```

```
import pandas as pd
```

```
df2 = pd.read_csv('/content/menu.csv')  
df2.head()
```

	Category	Item	Serving Size	Calories	Calories from Fat	Total Fat	Total Fat (% Daily Value)	Saturated Fat	Sat
0	Breakfast	Egg McMuffin	4.8 oz (136 g)	300	120	13.0	20	5.0	
1	Breakfast	Egg White Delight	4.8 oz (135 g)	250	70	8.0	12	3.0	
2	Breakfast	Sausage McMuffin	3.9 oz (111 g)	370	200	23.0	35	8.0	
3	Breakfast	Sausage McMuffin with Egg	5.7 oz (161 g)	450	250	28.0	43	10.0	
4	Breakfast	Sausage McMuffin with Egg Whites	5.7 oz (161 g)	400	210	23.0	35	8.0	

5 rows × 24 columns

## Introduction (Dataset 2)

Understanding the nutritional composition of food items is essential for promoting healthier eating habits and informed consumer decision-making. This dataset contains

detailed nutritional information for various menu items across different categories, including calories, fats, carbohydrates, sugars, protein, vitamins, and minerals.

The objective of this exploratory data analysis is to examine nutritional patterns, identify variability across menu items, and highlight key attributes that influence dietary quality. By applying descriptive statistics and visual analysis, the study aims to uncover insights related to calorie distribution, nutrient composition, and category-wise food characteristics.

The findings from this analysis can support data-driven decisions in menu planning, health awareness initiatives, and nutritional optimization.

```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 260 entries, 0 to 259
Data columns (total 24 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   Category        260 non-null    object  
 1   Item            260 non-null    object  
 2   Serving Size   260 non-null    object  
 3   Calories        260 non-null    int64  
 4   Calories from Fat  260 non-null    int64  
 5   Total Fat       260 non-null    float64 
 6   Total Fat (% Daily Value) 260 non-null    int64  
 7   Saturated Fat  260 non-null    float64 
 8   Saturated Fat (% Daily Value) 260 non-null    int64  
 9   Trans Fat       260 non-null    float64 
 10  Cholesterol    260 non-null    int64  
 11  Cholesterol (% Daily Value) 260 non-null    int64  
 12  Sodium          260 non-null    int64  
 13  Sodium (% Daily Value) 260 non-null    int64  
 14  Carbohydrates  260 non-null    int64  
 15  Carbohydrates (% Daily Value) 260 non-null    int64  
 16  Dietary Fiber  260 non-null    int64  
 17  Dietary Fiber (% Daily Value) 260 non-null    int64  
 18  Sugars          260 non-null    int64  
 19  Protein         260 non-null    int64  
 20  Vitamin A (% Daily Value) 260 non-null    int64  
 21  Vitamin C (% Daily Value) 260 non-null    int64  
 22  Calcium          260 non-null    int64  
 23  Iron (% Daily Value) 260 non-null    int64  
dtypes: float64(3), int64(18), object(3)
memory usage: 48.9+ KB
```

## Dataset 2 – Data Structure and Attributes

The Dataset 2 consists of **260 records** and **24 columns**, containing detailed information about menu items and their nutritional values.

- The dataset includes **categorical attributes** such as *Category*, *Item*, and *Serving Size*.
- A large number of **numerical features** represent nutritional information, including calories, fats, carbohydrates, sugars, protein, and vitamins.
- All columns contain **non-null values**, indicating that there are **no missing values** in the dataset.
- The presence of both integer and floating-point numerical features allows for meaningful statistical and distributional analysis.

Overall, the dataset is well-structured and suitable for exploratory data analysis without the need for extensive data cleaning.

```
df2.isnull().sum()
```

	0
<b>Category</b>	0
<b>Item</b>	0
<b>Serving Size</b>	0
<b>Calories</b>	0
<b>Calories from Fat</b>	0
<b>Total Fat</b>	0
<b>Total Fat (% Daily Value)</b>	0
<b>Saturated Fat</b>	0
<b>Saturated Fat (% Daily Value)</b>	0
<b>Trans Fat</b>	0
<b>Cholesterol</b>	0
<b>Cholesterol (% Daily Value)</b>	0
<b>Sodium</b>	0
<b>Sodium (% Daily Value)</b>	0
<b>Carbohydrates</b>	0
<b>Carbohydrates (% Daily Value)</b>	0
<b>Dietary Fiber</b>	0
<b>Dietary Fiber (% Daily Value)</b>	0
<b>Sugars</b>	0
<b>Protein</b>	0
<b>Vitamin A (% Daily Value)</b>	0
<b>Vitamin C (% Daily Value)</b>	0
<b>Calcium (% Daily Value)</b>	0
<b>Iron (% Daily Value)</b>	0

**dtype:** int64

## Missing Values Analysis (Dataset 2)

The missing values check indicates that **all columns contain zero null values**. This confirms that Dataset 2 is **complete and clean**, with no missing entries across categorical and numerical attributes.

As a result, the dataset does not require any imputation or removal of records before proceeding with exploratory data analysis.

```
df2.describe()
```

	Calories	Calories from Fat	Total Fat	Total Fat (% Daily Value)	Saturated Fat	Saturated Fat (% Daily Value)	T
<b>count</b>	260.000000	260.000000	260.000000	260.000000	260.000000	260.000000	260.000000
<b>mean</b>	368.269231	127.096154	14.165385	21.815385	6.007692	29.965385	29.965385
<b>std</b>	240.269886	127.875914	14.205998	21.885199	5.321873	26.639209	26.639209
<b>min</b>	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
<b>25%</b>	210.000000	20.000000	2.375000	3.750000	1.000000	4.750000	4.750000
<b>50%</b>	340.000000	100.000000	11.000000	17.000000	5.000000	24.000000	24.000000
<b>75%</b>	500.000000	200.000000	22.250000	35.000000	10.000000	48.000000	48.000000
<b>max</b>	1880.000000	1060.000000	118.000000	182.000000	20.000000	102.000000	102.000000

8 rows × 21 columns

## Descriptive Statistics (Dataset 2)

The descriptive statistics provide a comprehensive overview of the nutritional attributes of menu items.

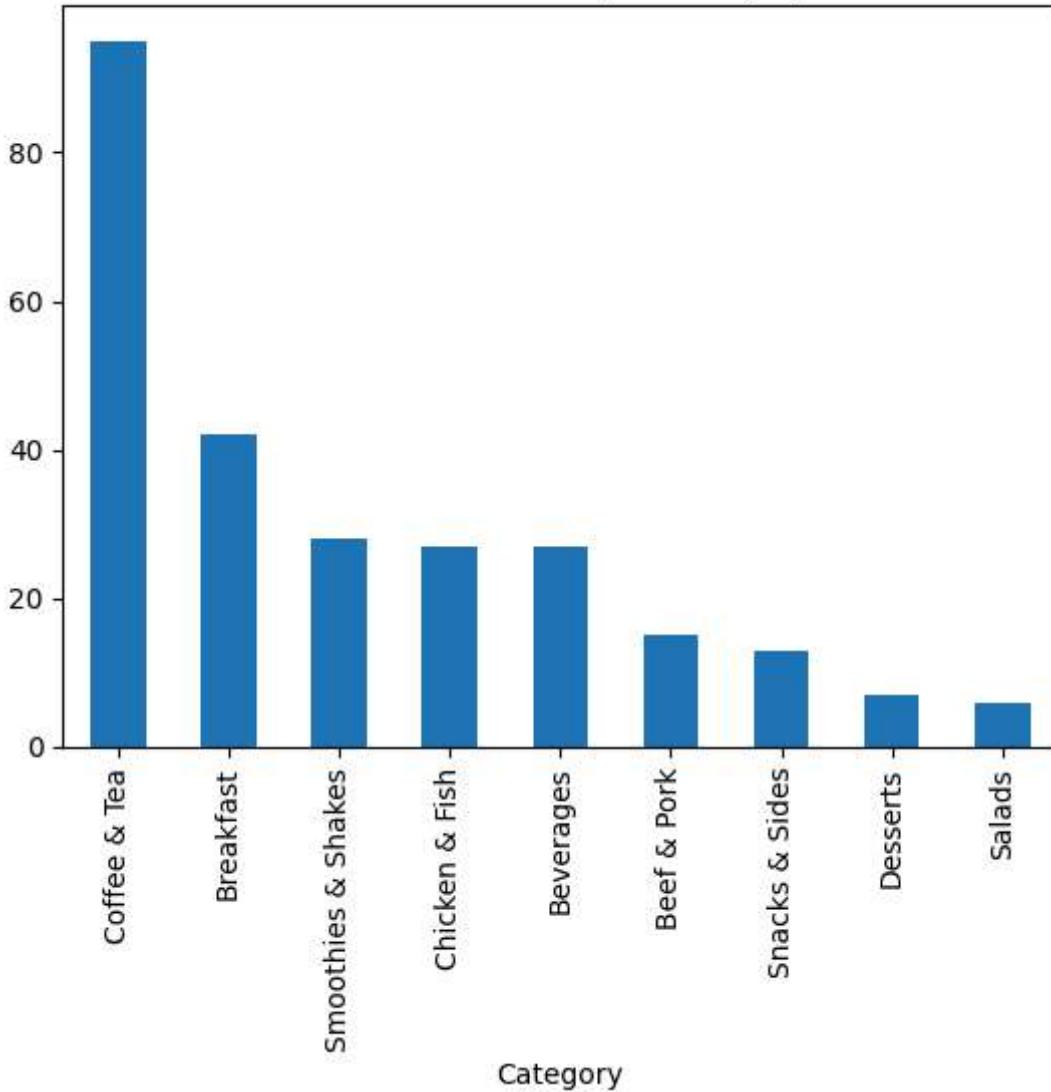
- The **average calorie content** per item is approximately **368 calories**, with values ranging from **0 to 1880 calories**, indicating a wide variation in menu offerings.
- Fat-related attributes show noticeable variability, with **Total Fat** averaging around **14 g**, and some items containing extremely high fat levels.
- Carbohydrate content averages **47 g**, while sugar levels average approximately **29 g**, suggesting that several items are high in sugar.
- Sodium levels show significant dispersion, with a maximum value reaching **3600 mg**, which exceeds recommended daily intake limits.
- Protein content averages around **13 g**, indicating moderate protein availability across items.
- Vitamin and mineral percentages vary widely, highlighting differences in nutritional quality among menu items.

Overall, the dataset exhibits **high variability across nutritional features**, making it suitable for further analysis and visualization to identify healthier and less healthy menu choices.

```
df2['Category'].value_counts().plot(kind='bar', title='Number of Items per Category')
```

```
<Axes: title={'center': 'Number of Items per Category'}, xlabel='Category'>
```

Number of Items per Category



### Category-wise Distribution of Menu Items

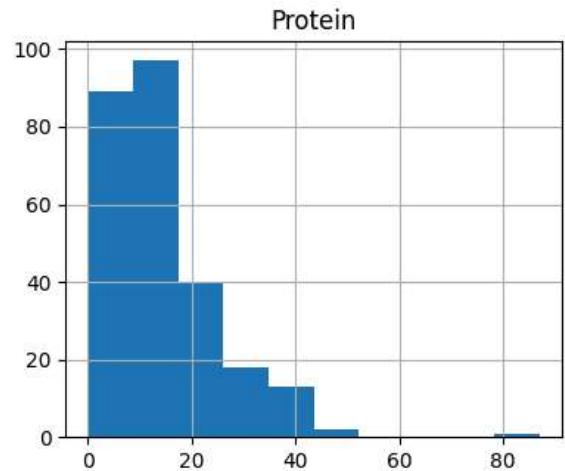
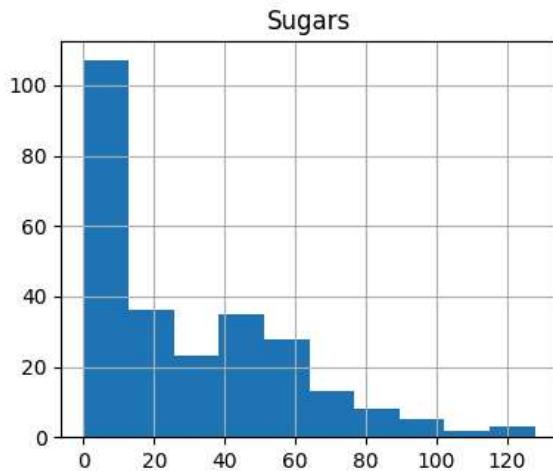
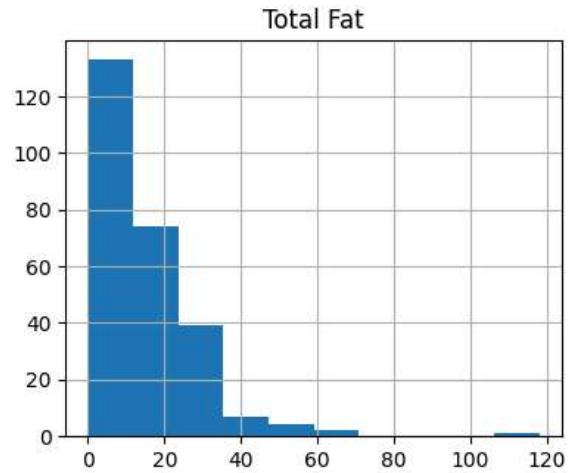
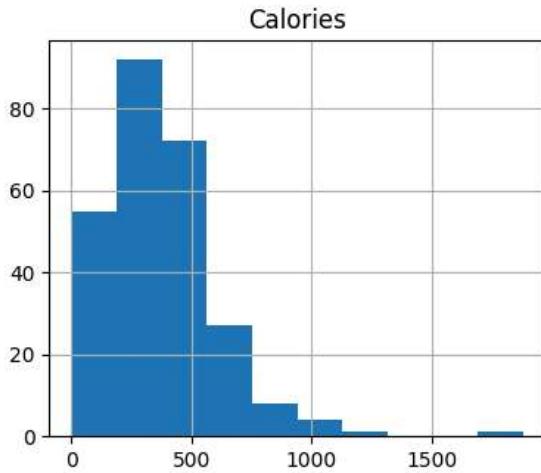
The bar chart illustrates the distribution of menu items across different food categories.

- Certain categories contain a **higher number of items**, indicating a broader variety offered in those sections.
- Categories with fewer items may represent **specialized or limited offerings**.
- This distribution helps in understanding how menu items are diversified across categories and which categories dominate the menu.

Such insights are useful for analyzing customer choices and for designing balanced or healthier menus.

```
df2[['Calories', 'Total Fat', 'Sugars', 'Protein']].hist(figsize=(10,8))
```

```
array([[[<Axes: title={'center': 'Calories'}>,
         <Axes: title={'center': 'Total Fat'}>],
        [<Axes: title={'center': 'Sugars'}>,
         <Axes: title={'center': 'Protein'}>]], dtype=object)
```



## Distribution of Key Nutritional Attributes

The histograms display the distribution of important nutritional attributes across menu items.

- **Calories** show a right-skewed distribution, indicating that while many items are moderate in calories, some items are extremely high in calorie content.
- **Total Fat** distribution suggests that most items contain low to moderate fat, with a few high-fat outliers.
- **Sugars** distribution highlights the presence of several items with high sugar content, which may impact dietary health.
- **Protein** levels are moderately distributed, indicating balanced protein availability across most menu items.