PROJECT - COFFEE SALES DATA ANALYSIS

Project Description:

This project is focused on analyzing the coffee sales data. This project aims to find data-driven solutions to improve coffee business by generating actionable insights from the data by understanding the sales and product performance, customer preference by coffee type, customer behaviour and purchasing patterns, and coffee shopping trends over the time. In this project, we are going to use EDA to discover the customer's purchasing patterns and sales trends which can aid in the inventory planning.

Tech Stack Used:

Ms. Excel, Python, pandas, matplotlib, seaborn, Power BI

Dataset Overview:

This dataset contains detailed records of coffee sales from a vending machine. The vending machine is the work of a dataset author who is committed to providing an open dataset to the community. It is intended for analysis of purchasing patterns, sales trends, and customer preferences related to coffee products. The dataset spans from March 2024 to July 2024, capturing daily transaction data.

Column Descriptions:

Column Name	Description
date	The date on which the transaction occurred
datetime	The exact timestamp (date & time) when the coffee was purchased
cash_type	Payment mode used for the transaction – card or cash
card	Unique customer ID for card users
money	Total amount spent in the transaction
coffee_name	Name of the coffee product purchased

Steps:

1. Importing Necessary Libraries
2. Data Collection & Data Understanding
3. Data Cleaning & Preprocessing
4. Exploratory Data Analysis (EDA)

Below are the steps followed and python codes for doing the analysis.

1. Importing Necessary Libraries

```
#Importing the necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
import warnings
warnings.filterwarnings('ignore')
```

2. Data Collection & Data Understanding

```
#Loading the dataset
coffee_data = pd.read_csv("index.csv")
coffee_data.head(5)
```

	date	datetime	cash_type	card	money	coffee_name
0	2024-03-01	2024-03-01 10:15:50.520	card	ANON-0000-0000-0001	38.7	Latte
1	2024-03-01	2024-03-01 12:19:22.539	card	ANON-0000-0000-0002	38.7	Hot Chocolate
2	2024-03-01	2024-03-01 12:20:18.089	card	ANON-0000-0000-0002	38.7	Hot Chocolate
3	2024-03-01	2024-03-01 13:46:33.006	card	ANON-0000-0000-0003	28.9	Americano
4	2024-03-01	2024-03-01 13:48:14.626	card	ANON-0000-0000-0004	38.7	Latte

```
#Understanding the data
coffee_data.shape
```

```
(1133, 6)
```

There are 1133 records and 6 columns in the dataset. The dataset spans from the start of March 2024 to the end of July 2024, capturing daily transaction data.

```
coffee_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1133 entries, 0 to 1132
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   date         1133 non-null   object 
 1   datetime     1133 non-null   object 
 2   cash_type    1133 non-null   object 
 3   card         1044 non-null   object 
 4   money        1133 non-null   float64
 5   coffee_name  1133 non-null   object 
dtypes: float64(1), object(5)
memory usage: 53.2+ KB
```

```
coffee_data.describe()
```

	money
count	1133.000000
mean	33.105808
std	5.035366
min	18.120000
25%	28.900000
50%	32.820000
75%	37.720000
max	40.000000

We loaded and understood the data and checked the data quality. The next step is to clean the data before doing the analysis.

3. Data Cleaning & Preprocessing

```python
# Convert date and datetime columns
coffee_data['date'] = pd.to_datetime(coffee_data['date'])
coffee_data['datetime'] = pd.to_datetime(coffee_data['datetime'])
```

```python
coffee_data.dtypes
```

```
date           datetime64[ns]
datetime       datetime64[ns]
cash_type              object
card                   object
money                 float64
coffee_name            object
dtype: object
```

```python
#Changing some column names for better understanding of the data
coffee_data = coffee_data.rename(columns={'date': 'transaction_date','cash_type': 'payment_type','money': 'transaction_amount'})
```

```python
coffee_data.head(2)
```

	transaction_date	datetime	payment_type	card	transaction_amount	coffee_name
0	2024-03-01	2024-03-01 10:15:50.520	card	ANON-0000-0000-0001	38.7	Latte
1	2024-03-01	2024-03-01 12:19:22.539	card	ANON-0000-0000-0002	38.7	Hot Chocolate

```python
coffee_data.tail(2)
```

	transaction_date	datetime	payment_type	card	transaction_amount	coffee_name
1131	2024-07-31	2024-07-31 21:54:11.824	card	ANON-0000-0000-0445	32.82	Latte
1132	2024-07-31	2024-07-31 21:55:16.570	card	ANON-0000-0000-0446	32.82	Latte

```python
#checking duplicates if any
coffee_data.duplicated().sum()
```

```
0
```

```python
# Check Missing Values
coffee_data.isnull().sum()
```

```
transaction_date       0
datetime               0
payment_type           0
card                  89
transaction_amount     0
coffee_name            0
dtype: int64
```

There are 89 null values in the card column.

```python
# Handling the missing values
coffee_data['card'] = coffee_data['card'].fillna('CASH_USER')
```

As the card column contains the customer ids of the card user customers, the other missing values are the customers who used cash as the purchasing medium. So these missing values are filled with 'CASH_USER'.

```python
coffee_data.isnull().sum()
```

```
transaction_date      0
datetime              0
payment_type          0
card                  0
transaction_amount    0
coffee_name           0
dtype: int64
```

There are no more missing values.

```python
# Feature Engineering
coffee_data['hour'] = coffee_data['datetime'].dt.hour
coffee_data['day'] = coffee_data['transaction_date'].dt.day
coffee_data['day_name'] = coffee_data['transaction_date'].dt.day_name()
coffee_data['month_name'] = coffee_data['transaction_date'].dt.month_name()
coffee_data['quarter'] = coffee_data['transaction_date'].dt.quarter
coffee_data['year'] = coffee_data['transaction_date'].dt.year
```

```python
coffee_data.head(3)
```

	transaction_date	datetime	payment_type	card	transaction_amount	coffee_name	hour	day	day_name	month_name	quarter	year
0	2024-03-01	2024-03-01 10:15:50.520	card	ANON-0000-0000-0001	38.7	Latte	10	1	Friday	March	1	2024
1	2024-03-01	2024-03-01 12:19:22.539	card	ANON-0000-0000-0002	38.7	Hot Chocolate	12	1	Friday	March	1	2024
2	2024-03-01	2024-03-01 12:20:18.089	card	ANON-0000-0000-0002	38.7	Hot Chocolate	12	1	Friday	March	1	2024

There are 4 quarters in a year. January, February, and March belong to quarter 1. April, May, and June belong to quarter 2. July, August, and September belong to quarter 3. October, November, and December belong to quarter 4.

Now the data cleaning and preprocessing is over. Next we are going to do Exploratory Data Analysis.

Next, we are going to explore and analyze the data to find insights from it.

4. Exploratory Data Analysis (EDA)

```python
#Check the time range of this dataset
[coffee_data['transaction_date'].min(),coffee_data['transaction_date'].max()]
```

```
[Timestamp('2024-03-01 00:00:00'), Timestamp('2024-07-31 00:00:00')]
```

The time range of this data set is from 2023-3-1 to 2024-7-31. The transaction details of purchased coffee products in this date range is given in the dataset.

```python
#Check the number of unique values in each column
coffee_data.nunique()
```

```
transaction_date       150
datetime              1133
payment_type             2
card                   447
transaction_amount      16
coffee_name              8
hour                    16
day                     31
day_name                 7
month_name               5
quarter                  3
year                     1
dtype: int64
```

```python
total_revenue = coffee_data['transaction_amount'].sum()
total_transactions = len(coffee_data)
avg_transaction = coffee_data['transaction_amount'].mean()
unique_customers = coffee_data['card'].nunique()


print(f"  • Total Revenue: ${total_revenue:,.2f}")
print(f"  • Total Transactions: {total_transactions:,}")
print(f"  • Average Transaction Value: ${avg_transaction:.2f}")
print(f"  • Unique Card Customers: {unique_customers}")
```

```
  • Total Revenue: $37,508.88
  • Total Transactions: 1,133
  • Average Transaction Value: $33.11
  • Unique Card Customers: 447
```

```python
coffee_data.loc[:,['payment_type','card','coffee_name']].describe().T
```

	count	unique	top	freq
payment_type	1133	2	card	1044
card	1133	447	CASH_USER	89
coffee_name	1133	8	Americano with Milk	268

```python
coffee_data['payment_type'].value_counts()
```

```
card     1044
cash       89
Name: payment_type, dtype: int64
```

```python
coffee_data['card'].value_counts()
```

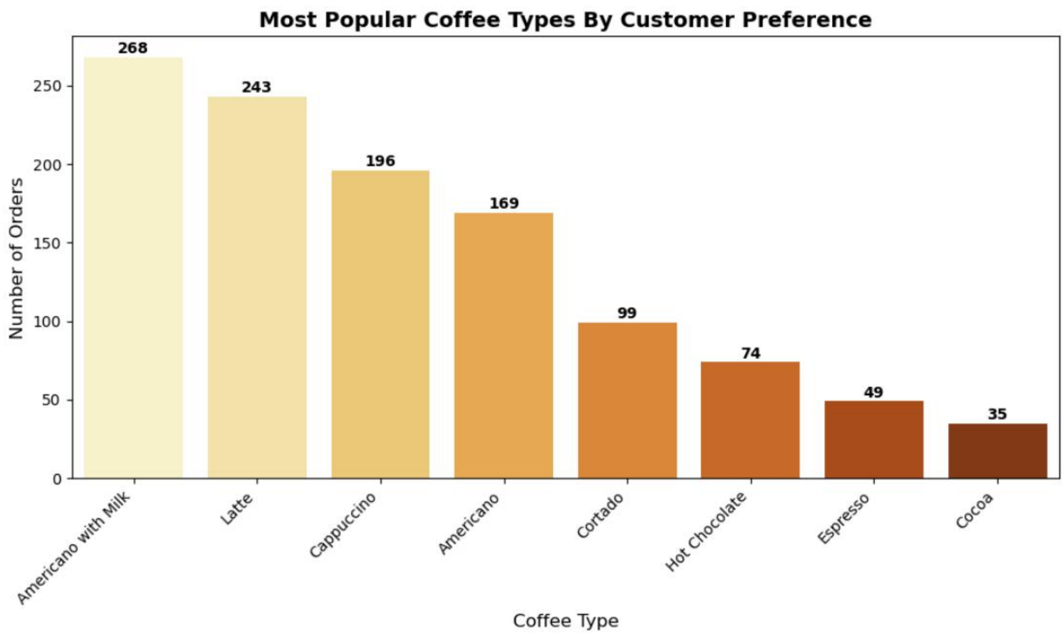
```
CASH_USER              89
ANON-0000-0000-0012    88
ANON-0000-0000-0009    63
ANON-0000-0000-0097    27
ANON-0000-0000-0003    23
                       ..
ANON-0000-0000-0196     1
ANON-0000-0000-0195     1
ANON-0000-0000-0193     1
ANON-0000-0000-0190     1
ANON-0000-0000-0446     1
Name: card, Length: 447, dtype: int64
```

```python
coffee_data['coffee_name'].value_counts()
```

```
Americano with Milk    268
Latte                  243
Cappuccino             196
Americano              169
Cortado                 99
Hot Chocolate           74
Espresso                49
Cocoa                   35
Name: coffee_name, dtype: int64
```

#Most Popular Coffee Types By Customer Preference

```
coffee_counts =coffee_data['coffee_name'].value_counts()
plt.figure(figsize=(10, 6))
ax = sns.barplot(x=coffee_counts.index, y=coffee_counts.values, palette='YlOrBr')


for i, v in enumerate(coffee_counts.values):
   ax.text(i, v + 0.5, str(v), ha='center', va='bottom', fontsize=10, fontweight='bold', color='black')

plt.title('Most Popular Coffee Types By Customer Preference', fontsize=14, fontweight='bold')
plt.xlabel('Coffee Type', fontsize=12)
plt.ylabel('Number of Orders', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



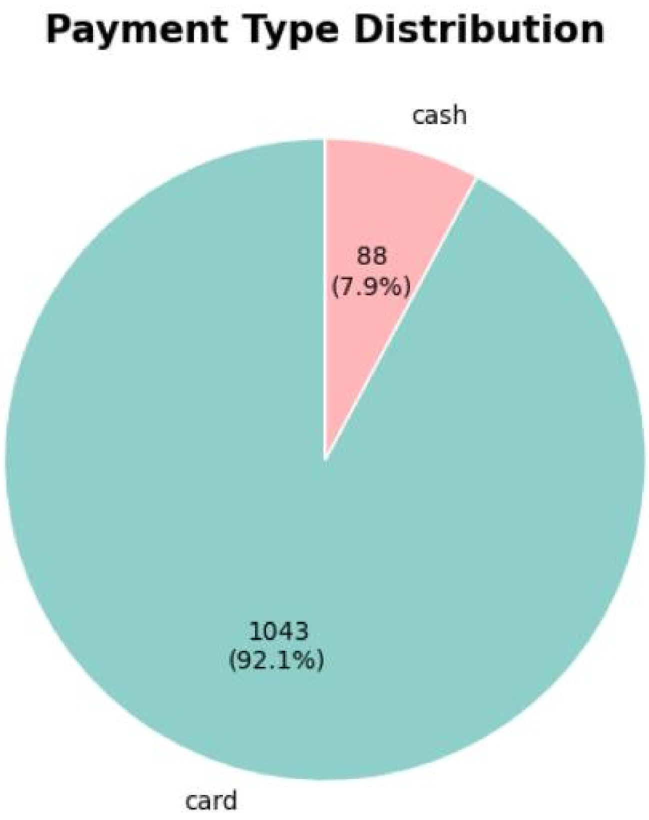
Insights:
The most preferred coffee type is Americano with Milk followed by Latte. The least preferred coffee type by customers is Cocoa.

Distribution of Payment Type

```python
payment_dist = coffee_data['payment_type'].value_counts()
print("\n PAYMENT TYPE DISTRIBUTION:")
for payment, count in payment_dist.items():
    percentage = (count / len(coffee_data)) * 100
    print(f"  • {payment.capitalize()}: {count} ({percentage:.1f}%)")
```

```
PAYMENT TYPE DISTRIBUTION:
  • Card: 1044 (92.1%)
  • Cash: 89 (7.9%)
```

```python
#Payment Type Distribution

payment_dist = coffee_data['payment_type'].value_counts()


plt.figure(figsize=(5,5))
plt.pie(
    payment_dist,
    labels=payment_dist.index,
    autopct=lambda p: f'{int(p * sum(payment_dist)/100)}\n({p:.1f}%)',
    startangle=90,
    colors=['#8ECFC9', '#FFB6B9'],
    wedgeprops={'edgecolor': 'white'}
)

plt.title("Payment Type Distribution", fontsize=15, fontweight='bold')
plt.tight_layout()
plt.show()
```



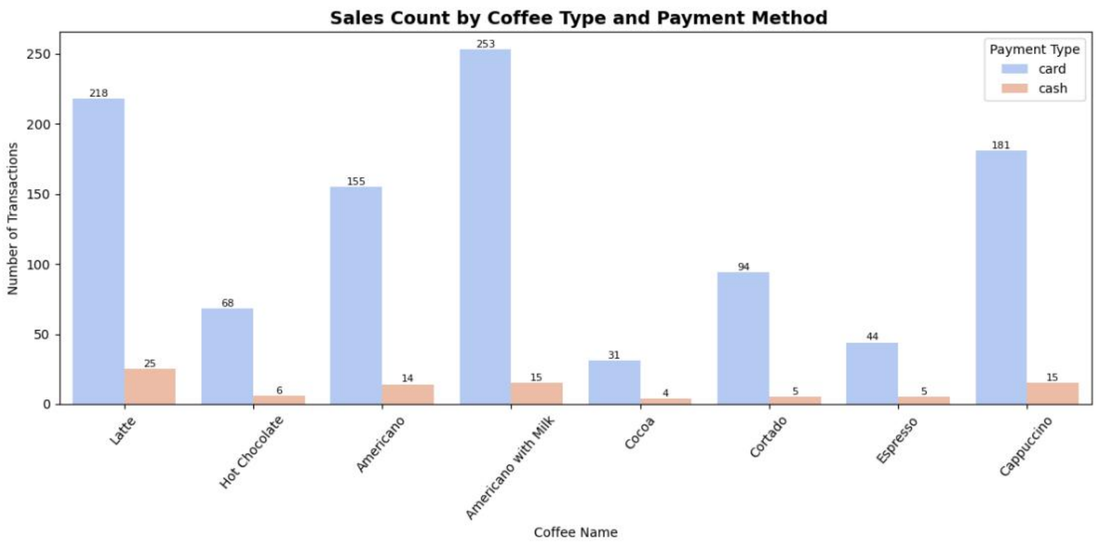
Insights:
Most customers prefer card as payment type. Only 7.9% transactions are using cash and the rest 92.1% transactions are using card.

```
coffee_data[['payment_type','coffee_name']].value_counts()
```

```
payment_type  coffee_name
card          Americano with Milk    253
              Latte                  218
              Cappuccino             181
              Americano              155
              Cortado                 94
              Hot Chocolate           68
              Espresso                44
              Cocoa                   31
cash          Latte                   25
              Americano with Milk     15
              Cappuccino              15
              Americano               14
              Hot Chocolate            6
              Cortado                  5
              Espresso                 5
              Cocoa                    4
dtype: int64
```

Insights:
The most preferred coffee type by card users are Americano with Milk. The most preferred coffee type by cash users are Latte.

```
#Sales by Coffee type and payment type
plt.figure(figsize=(12,6))
ax = sns.countplot(
    data=coffee_data,
    x='coffee_name',
    hue='payment_type',
    dodge=True,
    palette='coolwarm'
)
plt.title(' Sales Count by Coffee Type and Payment Method', fontsize=14, fontweight='bold')
plt.xlabel('Coffee Name')
plt.ylabel('Number of Transactions')
plt.xticks(rotation=50)
plt.legend(title='Payment Type')
plt.tight_layout()


for p in ax.patches:
    height = p.get_height()
    if height > 0:
        ax.text(
            p.get_x() + p.get_width() / 2,
            height + 0.2,
            f'{int(height)}',
            ha='center', va='bottom', fontsize=8
        )

plt.show()
```

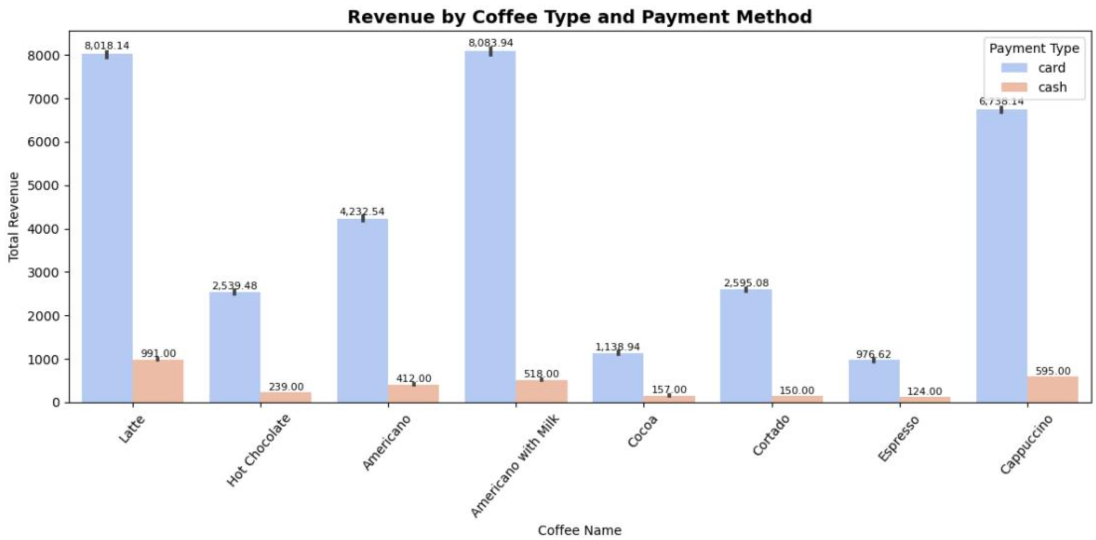


```
pivot_table = coffee_data.pivot_table(values='transaction_amount', index='coffee_name', columns='payment_type', aggfunc='sum')
print(pivot_table)
```

```
payment_type           card   cash
coffee_name
Americano           4232.54  412.0
Americano with Milk 8083.94  518.0
Cappuccino          6738.14  595.0
Cocoa               1138.94  157.0
Cortado             2595.08  150.0
Espresso             976.62  124.0
Hot Chocolate       2539.48  239.0
Latte               8018.14  991.0
```

#Revenue by Coffee type and payment type

```
plt.figure(figsize=(12,6))
ax = sns.barplot(
   data=coffee_data,
   x='coffee_name',
   y='transaction_amount',
   hue='payment_type',
   dodge=True,
   palette='coolwarm',
   estimator=sum
)

plt.title('Revenue by Coffee Type and Payment Method', fontsize=14,
fontweight='bold')
plt.xlabel('Coffee Name')
plt.ylabel('Total Revenue')
plt.xticks(rotation=50)
plt.legend(title='Payment Type')
plt.tight_layout()


for p in ax.patches:
   height = p.get_height()
   if height > 0:
      ax.text(
         p.get_x() + p.get_width() / 2,
         height + (0.01 * height),
         f'{height:,.2f}',
         ha='center',
         va='bottom',
         fontsize=8
      )

plt.show()
```



Insights:

Considering the card transactions, the coffee type which brought higher revenue is Americano with Milk. Considering the cash transactions, the coffee type which brought higher revenue is Latte.

```
# Total sales (count of transactions) by payment method
sales_by_payment = coffee_data.groupby('payment_type')['transaction_date'].count().reset_index()
sales_by_payment.columns = ['payment_type', 'total_sales']
print("Total Sales by Payment Method:")
print(sales_by_payment)

# Total revenue (sum of transaction amounts) by payment method
revenue_by_payment = coffee_data.groupby('payment_type')['transaction_amount'].sum().reset_index()
revenue_by_payment.columns = ['payment_type', 'total_revenue']
print("\nTotal Revenue by Payment Method:")
print(revenue_by_payment)
```

```
Total Sales by Payment Method:
  payment_type  total_sales
0         card         1044
1         cash           89

Total Revenue by Payment Method:
  payment_type  total_revenue
0         card       34322.88
1         cash        3186.00
```

Insights:

Most revenue and sales are from transactions via card payment type.

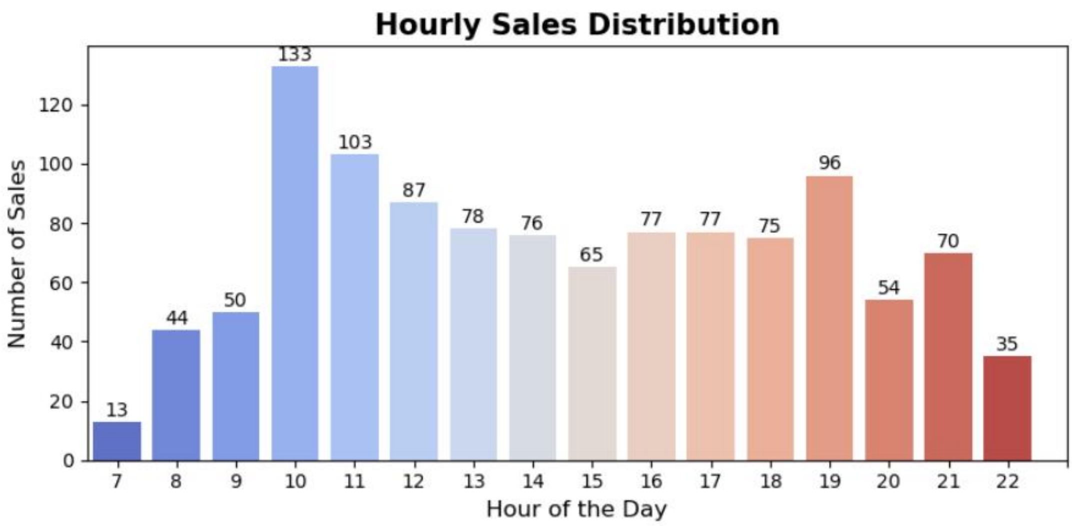
Analyzing Sales Trends Over Time

1)Hourly Sales

hourly_sales =coffee_data.groupby(['hour']).count()['transaction_date'].reset_index().rename(columns={'transaction_date':'count'})
hourly_sales

	hour	count
0	7	13
1	8	44
2	9	50
3	10	133
4	11	103
5	12	87
6	13	78
7	14	76
8	15	65
9	16	77
10	17	77
11	18	75
12	19	96
13	20	54
14	21	70
15	22	35

```python
#Hourly Sales distribution
hourly_sales = coffee_data.groupby('hour').size()

plt.figure(figsize=(8, 4))
ax = sns.barplot(x=hourly_sales.index, y=hourly_sales.values, palette='coolwarm')


for i, v in enumerate(hourly_sales.values):
    ax.text(i, v + 0.5, str(v), ha='center', va='bottom', fontsize=10, fontweight='normal')

plt.title('Hourly Sales Distribution', fontsize=15, fontweight='bold')
plt.xlabel('Hour of the Day', fontsize=12)
plt.ylabel('Number of Sales', fontsize=12)
plt.xticks(range(0, 17))
plt.tight_layout()
plt.show()
```



```python
# Peak Hours Analysis
print("\n PEAK SALES HOURS:")
peak_hours = coffee_data.groupby('hour').size().sort_values(ascending=False).head(3)
for hour, count in peak_hours.items():
    print(f"  • {hour}:00 - {count} sales")
```

```
 PEAK SALES HOURS:
  • 10:00 - 133 sales
  • 11:00 - 103 sales
  • 19:00 - 96 sales
```

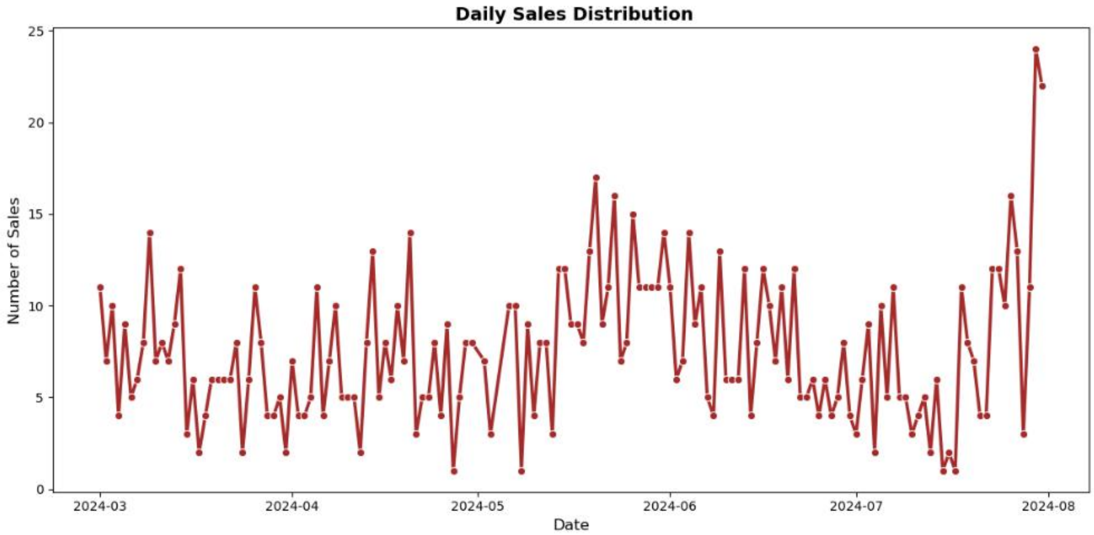
Peak sales hours are 10,11, and 19. Least sales hours are 7,22, and 8. This means the sales are less during early morning and late night.

2) Daily Sales

```python
coffee_data['transaction_date'].value_counts()
```

```
2024-07-30    24
2024-07-31    22
2024-05-20    17
2024-07-26    16
2024-05-23    16
              ..
2024-07-13     2
2024-05-08     1
2024-07-17     1
2024-07-15     1
2024-04-27     1
Name: transaction_date, Length: 150, dtype: int64
```

```python
# Daily Sales Distribution
daily_sales = coffee_data.groupby('transaction_date').size().reset_index(name='sales_count')


plt.figure(figsize=(12,6))
sns.lineplot(x='transaction_date', y='sales_count', data=daily_sales, color='brown', linewidth=2.5, marker='o')

plt.title(' Daily Sales Distribution', fontsize=14, fontweight='bold')
plt.xlabel('Date', fontsize=12)
plt.ylabel('Number of Sales', fontsize=12)
plt.tight_layout()
plt.show()
```



```python
# Count total sales per transaction_date
daily_sales_count = coffee_data.groupby('transaction_date').size().reset_index(name='sales_count')

# Date with highest sales
max_sales_date = daily_sales_count.loc[daily_sales_count['sales_count'].idxmax()]

# Date with lowest sales
min_sales_date = daily_sales_count.loc[daily_sales_count['sales_count'].idxmin()]

print("Date with highest sales:")
print(max_sales_date)

print("\nDate with lowest sales:")
print(min_sales_date)
```

```
Date with highest sales:
transaction_date    2024-07-30 00:00:00
sales_count                          24
Name: 148, dtype: object

Date with lowest sales:
transaction_date    2024-04-27 00:00:00
sales_count                           1
Name: 57, dtype: object
```

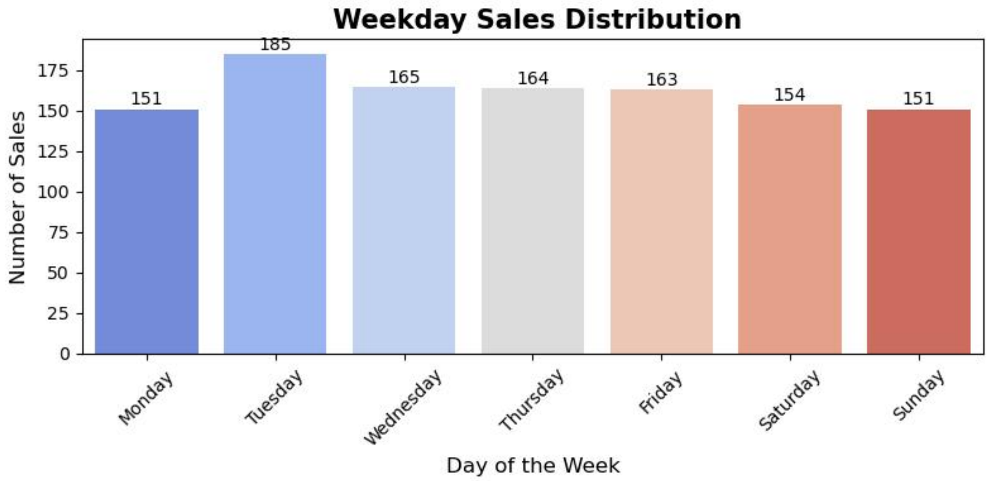
Sales have increased by the end of July.

3) Weekday Sales

weekday_sales
=coffee_data.groupby(['day_name']).count()['transaction_date'].reset_index().rena
me(columns={'transaction_date':'count'})
weekday_sales

	day_name	count
0	Friday	163
1	Monday	151
2	Saturday	154
3	Sunday	151
4	Thursday	164
5	Tuesday	185
6	Wednesday	165

```python
#Weekday Sales Distribution
weekday_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']


weekday_sales = coffee_data.groupby('day_name').size().reindex(weekday_order)

plt.figure(figsize=(8, 4))
ax = sns.barplot(x=weekday_sales.index, y=weekday_sales.values, palette='coolwarm')


for i, v in enumerate(weekday_sales.values):
    ax.text(i, v + 0.2, str(v), ha='center', va='bottom', fontsize=10, fontweight='normal')

plt.title(' Weekday Sales Distribution', fontsize=15, fontweight='bold')
plt.xlabel('Day of the Week', fontsize=12)
plt.ylabel('Number of Sales', fontsize=12)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```




```python
# Best sales Day Analysis
print("\n BEST SALES DAYS:")
best_days = coffee_data.groupby('day_name').size().sort_values(ascending=False).head(3)
for day, count in best_days.items():
    print(f"  • {day}: {count} sales")
```

```
 BEST SALES DAYS:
  • Tuesday: 185 sales
  • Wednesday: 165 sales
  • Thursday: 164 sales
```

Insights:

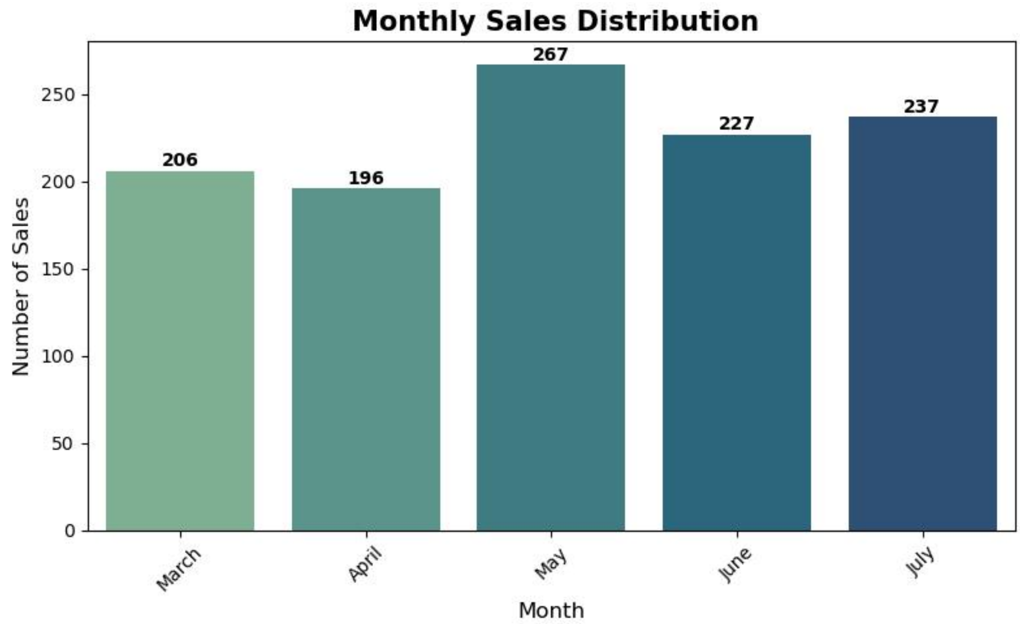
Sales are highest from Tuesday to Thursday, which shows that people buy more coffee during their regular workdays. Sales drop on Monday and Sunday, likely because people start the week slowly on Monday and stay at home or relax on Sunday. This indicates that coffee purchases are mainly driven by work-week routines rather than weekend leisure.

4) Monthly Sales

monthly_sales
=coffee_data.groupby(['month_name']).count()['transaction_date'].reset_index().rename(columns={'transaction_date':'count'})
monthly_sales

	month_name	count
0	April	196
1	July	237
2	June	227
3	March	206
4	May	267

```
#Monthly Sales Distribution

month_order = ['March', 'April', 'May', 'June', 'July']


monthly_sales = (
    coffee_data.groupby('month_name')['transaction_date']
    .count()
    .reindex(month_order)
    .reset_index()
    .rename(columns={'transaction_date': 'sales_count'})
)


plt.figure(figsize=(8, 5))
ax = sns.barplot(x='month_name', y='sales_count', data=monthly_sales,
palette='crest')


for i, v in enumerate(monthly_sales['sales_count']):
    ax.text(i, v + 0.5, str(v), ha='center', va='bottom', fontsize=10, fontweight='bold')

plt.title(' Monthly Sales Distribution', fontsize=15, fontweight='bold')
plt.xlabel('Month', fontsize=12)
plt.ylabel('Number of Sales', fontsize=12)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Insights:
Sales are highest in May and lowest in April. Sales also remain high in June and July. This may indicate a seasonal pattern. However, we do not have weather data to confirm whether this increase is due to rainy season effects.

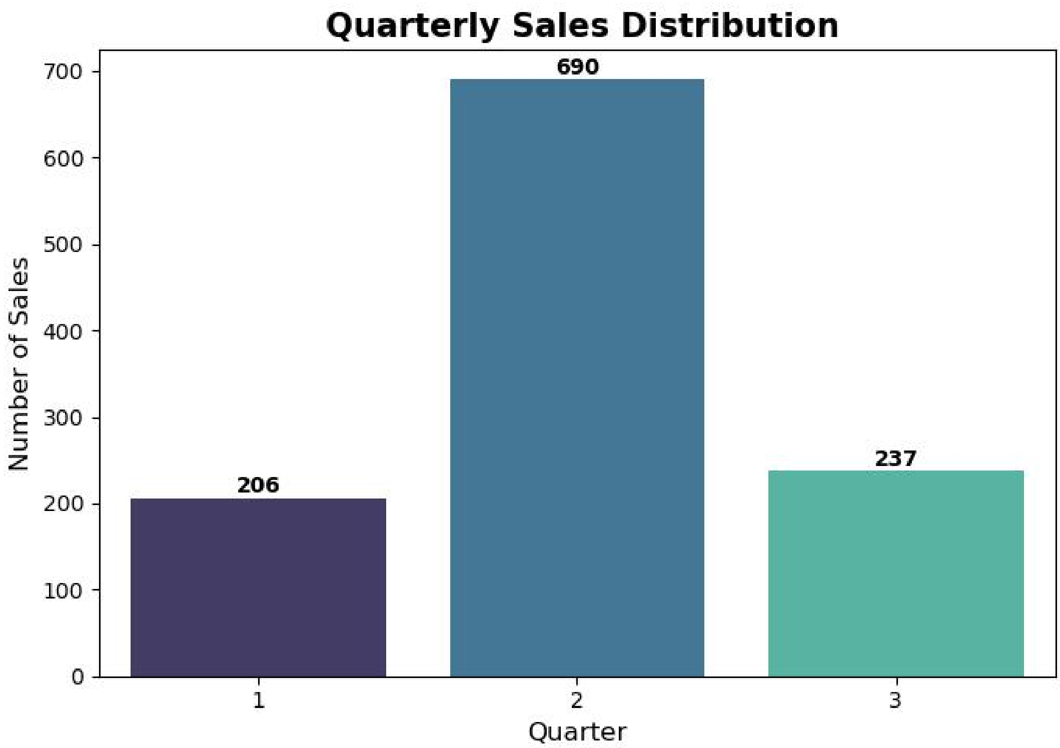
5) Quarterly Sales

```
quarterly_sales
=coffee_data.groupby(['quarter']).count()['transaction_date'].reset_index().rename(
columns={'transaction_date':'count'})
quarterly_sales
```

	quarter	count
0	1	206
1	2	690
2	3	237

```
#Quarterly Sales Distribution

quarterly_sales = (
    coffee_data.groupby('quarter')['transaction_date']
    .count()
    .reset_index()
    .rename(columns={'transaction_date': 'sales_count'})
)


quarterly_sales = quarterly_sales.sort_values('quarter')
```

```
plt.figure(figsize=(7, 5))
ax = sns.barplot(x='quarter', y='sales_count', data=quarterly_sales, palette='mako')


for i, v in enumerate(quarterly_sales['sales_count']):
    ax.text(i, v + 0.5, str(v), ha='center', va='bottom', fontsize=10, fontweight='bold')

plt.title(' Quarterly Sales Distribution', fontsize=15, fontweight='bold')
plt.xlabel('Quarter', fontsize=12)
plt.ylabel('Number of Sales', fontsize=12)
plt.tight_layout()
plt.show()
```



Insights:
Quarter 2(April-June) has highest sales. This indicates that coffee sales peak strongly during the middle of the year. April to June, which includes the summer period and the start of the rainy season. During this time, people are more active outside, workplaces operate at full capacity, and customers tend to buy more coffee.

6) Yearly Sales

```
yearly_sales
=coffee_data.groupby(['year']).count()['transaction_date'].reset_index().rename(col
umns={'transaction_date':'count'})
yearly_sales
```

	year	count
0	2024	1133

Analyzing Revenue Trends Over Time

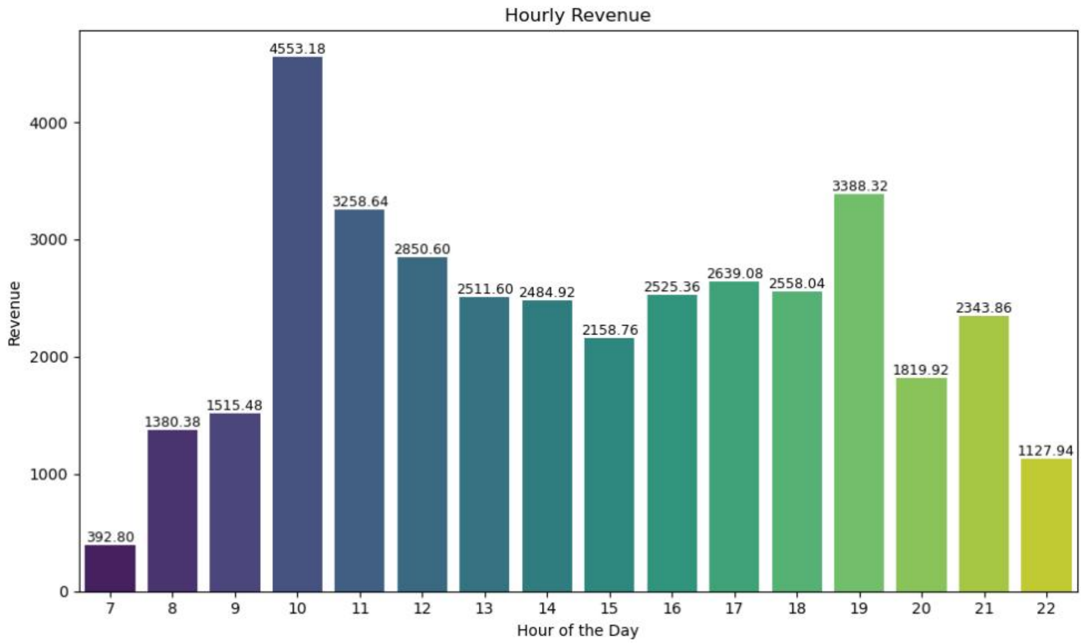
1) Hourly Revenue

```
hourly_revenue = (coffee_data.groupby('hour')['transaction_amount'].sum().reset_index().rename(columns={'transaction_amount': 'revenue'}))
hourly_revenue
```

	hour	revenue
0	7	392.80
1	8	1380.38
2	9	1515.48
3	10	4553.18
4	11	3258.64
5	12	2850.60
6	13	2511.60
7	14	2484.92
8	15	2158.76
9	16	2525.36
10	17	2639.08
11	18	2558.04
12	19	3388.32
13	20	1819.92
14	21	2343.86
15	22	1127.94

```
#Revenue Generated by Hours

hourly_revenue = hourly_revenue.sort_values('hour')

plt.figure(figsize=(10, 6))
sns.barplot(x='hour', y='revenue', data=hourly_revenue, palette='viridis')


for i, row in hourly_revenue.iterrows():
    plt.text(x=i, y=row['revenue'] + 0.01, s=f"{row['revenue']:.2f}", ha='center', va='bottom', fontsize=9)

plt.xlabel('Hour of the Day')
plt.ylabel('Revenue')
plt.title('Hourly Revenue')
plt.tight_layout()
```

```
plt.show()
```



Insights:

The most revenue generating hour is 10 followed by 19 and 11. The least revenue generating hours are 7 followed by 22.

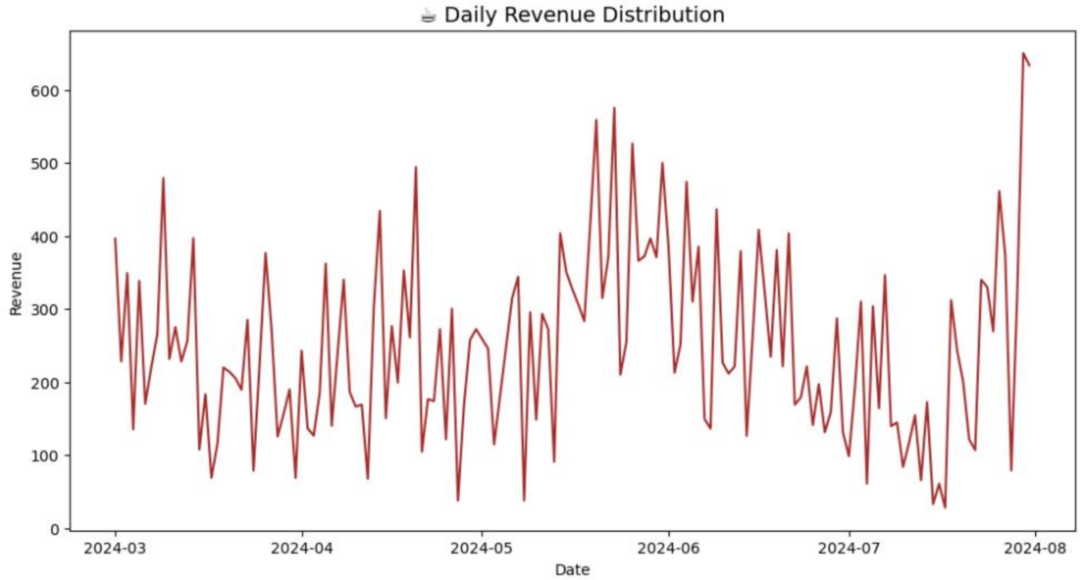
2) Daily Revenue

```
daily_revenue = (coffee_data.groupby('transaction_date')['transaction_amount'].sum().reset_index().rename(columns={'transaction_amount': 'revenue'}))
daily_revenue
```

	transaction_date	revenue
0	2024-03-01	396.30
1	2024-03-02	228.10
2	2024-03-03	349.10
3	2024-03-04	135.20
4	2024-03-05	338.50
...	...	...
145	2024-07-27	372.76
146	2024-07-28	78.86
147	2024-07-29	321.82
148	2024-07-30	650.48
149	2024-07-31	633.84

150 rows × 2 columns

```
#Daily Revenue Distribution
daily_revenue = coffee_data.groupby('transaction_date')['transaction_amount'].sum().reset_index()
plt.figure(figsize=(12,6))
sns.lineplot(x='transaction_date', y='transaction_amount', data=daily_revenue, color='brown')
plt.title(' Daily Revenue Distribution', fontsize=14)
plt.xlabel('Date')
plt.ylabel('Revenue')
plt.show()
```



Revenue increased by the end of July.

3) Weekday Revenue

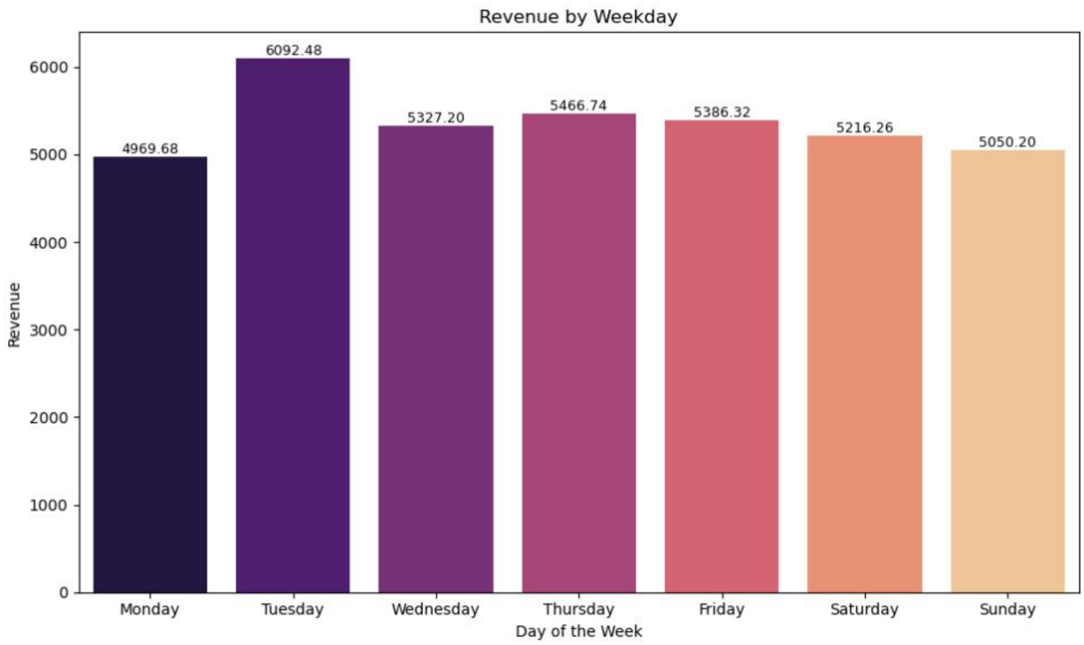
weekday_revenue = (coffee_data.groupby('day_name')['transaction_amount'].sum().reset_index().rename(columns={'transaction_amount': 'revenue'}))
weekday_revenue

	day_name	revenue
0	Friday	5386.32
1	Monday	4969.68
2	Saturday	5216.26
3	Sunday	5050.20
4	Thursday	5466.74
5	Tuesday	6092.48
6	Wednesday	5327.20

#Weekday Revenue Distribution

weekday_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']
weekday_revenue['day_name'] = pd.Categorical(weekday_revenue['day_name'], categories=weekday_order, ordered=True)
weekday_revenue = weekday_revenue.sort_values('day_name')

```
plt.figure(figsize=(10, 6))
ax = sns.barplot(x='day_name', y='revenue', data=weekday_revenue, palette='magma')


for p in ax.patches:
    height = p.get_height()
    ax.text(
        x=p.get_x() + p.get_width()/2,
        y=height + 0.01,
        s=f"{height:.2f}",
        ha='center',
        va='bottom',
        fontsize=9
    )

plt.xlabel('Day of the Week')
plt.ylabel('Revenue')
plt.title('Revenue by Weekday')
plt.tight_layout()
plt.show()
```



The weekday in which the most revenue generated is Tuesday.

4) Monthly Revenue

```
monthly_revenue = (coffee_data.groupby('month_name')['transaction_amount'].sum().reset_index().rename(columns={'transaction_amount': 'revenue'}))
monthly_revenue
```

	month_name	revenue
0	April	6720.56
1	July	6915.94
2	June	7758.76
3	March	7050.20
4	May	9063.42

```
#Monthly Revenue Distribution

month_order = ['March', 'April', 'May', 'June','July']

monthly_revenue['month_name'] = pd.Categorical(monthly_revenue['month_name'], categories=month_order, ordered=True)
monthly_revenue = monthly_revenue.sort_values('month_name')


plt.figure(figsize=(12, 6))
ax = sns.barplot(x='month_name', y='revenue', data=monthly_revenue, palette='coolwarm')


for p in ax.patches:
   height = p.get_height()
   ax.text(
      x=p.get_x() + p.get_width()/2,
      y=height + 0.01,
      s=f"{height:.2f}",
      ha='center',
      va='bottom',
      fontsize=9
   )

plt.xlabel('Month')
plt.ylabel('Revenue')
plt.title('Monthly Revenue')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

The month in which the most revenue generated is May.

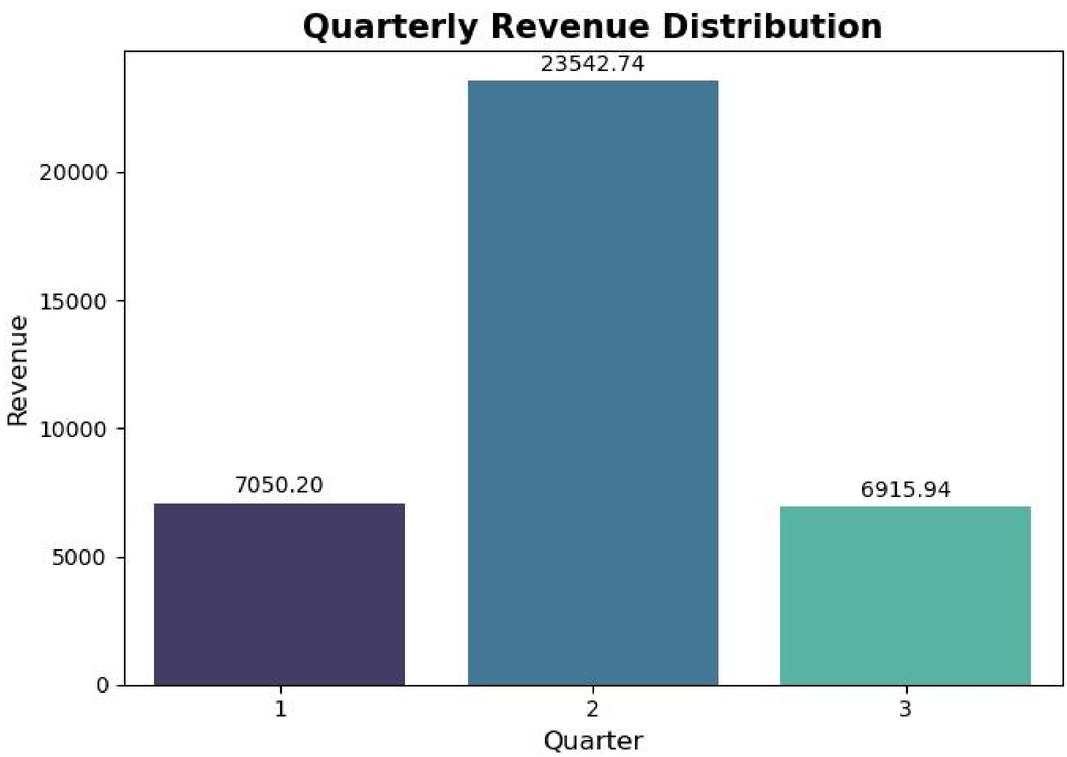
5) Quarterly Revenue

```
quarterly_revenue = (coffee_data.groupby('quarter')['transaction_amount'].sum().reset_index().rename(columns={'transaction_amount': 'revenue'}))
quarterly_revenue
```

	quarter	revenue
0	1	7050.20
1	2	23542.74
2	3	6915.94

```
#Quarterly Revenue Distribution

quarterly_revenue = (coffee_data.groupby('quarter')['transaction_amount']
                     .sum()
                     .reset_index()
                     .rename(columns={'transaction_amount': 'revenue'}))


quarterly_revenue = quarterly_revenue.sort_values('quarter')


plt.figure(figsize=(7, 5))
ax = sns.barplot(x='quarter', y='revenue', data=quarterly_revenue, palette='mako')


for i, v in enumerate(quarterly_revenue['revenue']):
   ax.text(i, v + 0.01*quarterly_revenue['revenue'].max(), f'{v:.2f}',
        ha='center', va='bottom', fontsize=10, fontweight='normal')
```

```
plt.title('Quarterly Revenue Distribution', fontsize=15, fontweight='bold')
plt.xlabel('Quarter', fontsize=12)
plt.ylabel('Revenue', fontsize=12)
plt.tight_layout()
plt.show()
```



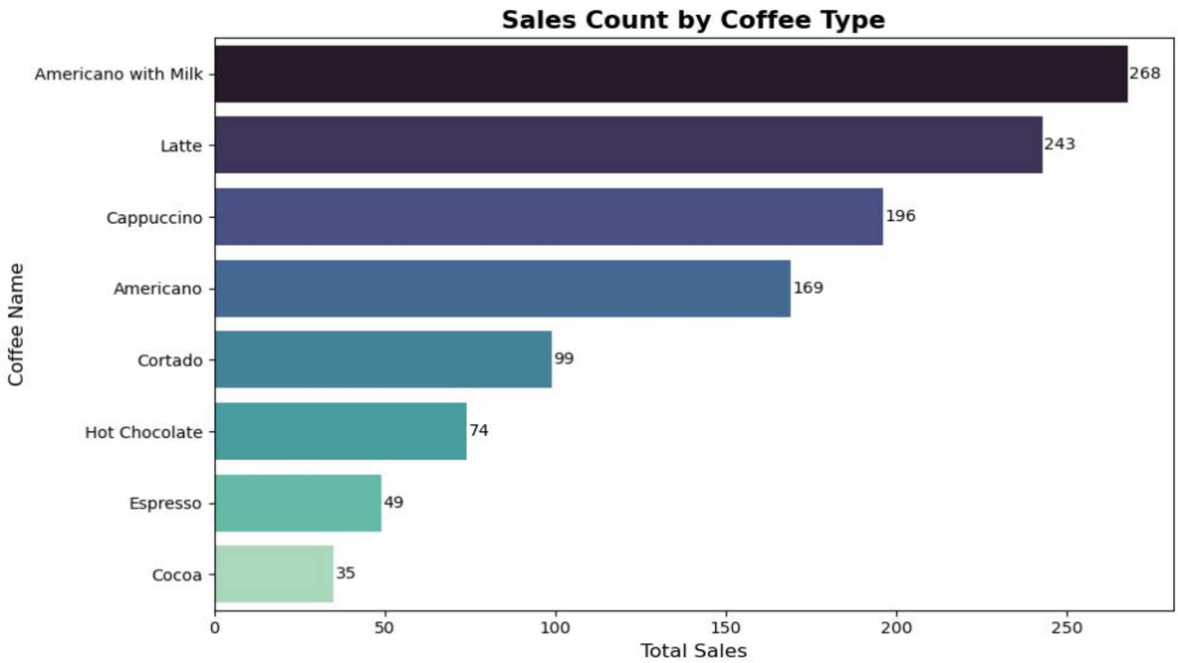
The quarter in which the most revenue generated is 2nd quarter.

6) Yearly Revenue

```
yearly_revenue = (coffee_data.groupby('year')['transaction_amount'].sum().reset_index().rename(columns={'transaction_amount': 'revenue'}))
yearly_revenue
```

	year	revenue
0	2024	37508.88

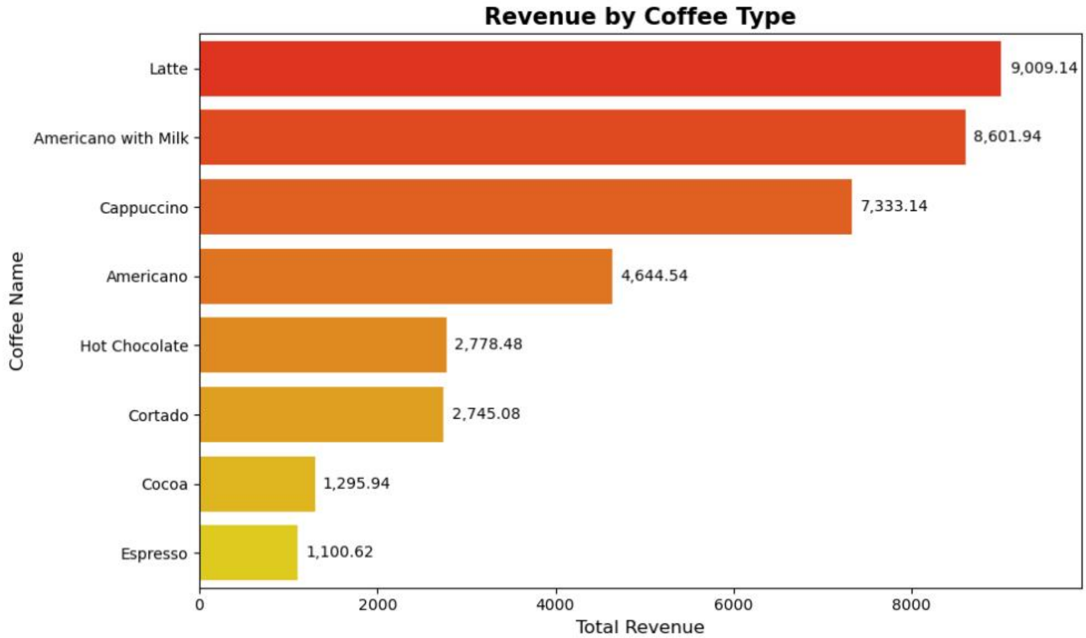
```
#Number of Sales by Coffee Type

coffee_sales = coffee_data['coffee_name'].value_counts().reset_index()
coffee_sales.columns = ['coffee_name', 'total_sales']


plt.figure(figsize=(10,6))
ax = sns.barplot(y='coffee_name', x='total_sales', data=coffee_sales, palette='mako')


for i, v in enumerate(coffee_sales['total_sales']):
    ax.text(v + 0.5, i, f'{v}', va='center', fontsize=10, fontweight='normal')  # slightly right of the bar


plt.title('Sales Count by Coffee Type', fontsize=15, fontweight='bold')
plt.xlabel('Total Sales', fontsize=12)
plt.ylabel('Coffee Name', fontsize=12)
plt.tight_layout()
plt.show()
```



The best-selling coffee type is Americano with Milk followed by Latte.

```
#Total Revenue by Coffee Type

coffee_revenue = coffee_data.groupby('coffee_name')['transaction_amount'] \
                    .sum() \
                    .sort_values(ascending=False) \
                    .reset_index()


plt.figure(figsize=(10,6))
ax = sns.barplot(y='coffee_name', x='transaction_amount', data=coffee_revenue, palette='autumn')


max_val = coffee_revenue['transaction_amount'].max()
```

```
ax.set_xlim(0, max_val * 1.1)


for i, v in enumerate(coffee_revenue['transaction_amount']):
    ax.text(v + 0.01*max_val, i, f'{v:,.2f}',
            va='center', fontsize=10, fontweight='normal')


plt.title('Revenue by Coffee Type', fontsize=15, fontweight='bold')
plt.xlabel('Total Revenue', fontsize=12)
plt.ylabel('Coffee Name', fontsize=12)
plt.tight_layout()
plt.show()
```



Latte is the most revenue generating coffee type followed by Americano with Milk.

```
#Average Money that Customers Spent per Coffee Type
average_money_per_coffee = coffee_data.groupby('coffee_name')['transaction_amount'].mean().sort_values(ascending=False)
print("Average Money Spent per Coffee Type:\n", average_money_per_coffee)
```

```
Average Money Spent per Coffee Type:
 coffee_name
Hot Chocolate          37.547027
Cappuccino             37.413980
Latte                  37.074650
Cocoa                  37.026857
Americano with Milk    32.096791
Cortado                27.728081
Americano              27.482485
Espresso               22.461633
Name: transaction_amount, dtype: float64
```

Customers spend the most on Hot Chocolate, Cappuccino, Latte, and Cocoa, with an average spending of around 37 dollars per transaction. The lowest average spending is on Espresso (22 dollars), which indicates that premium and milk-based drinks generate higher revenue per order compared to basic coffee types.

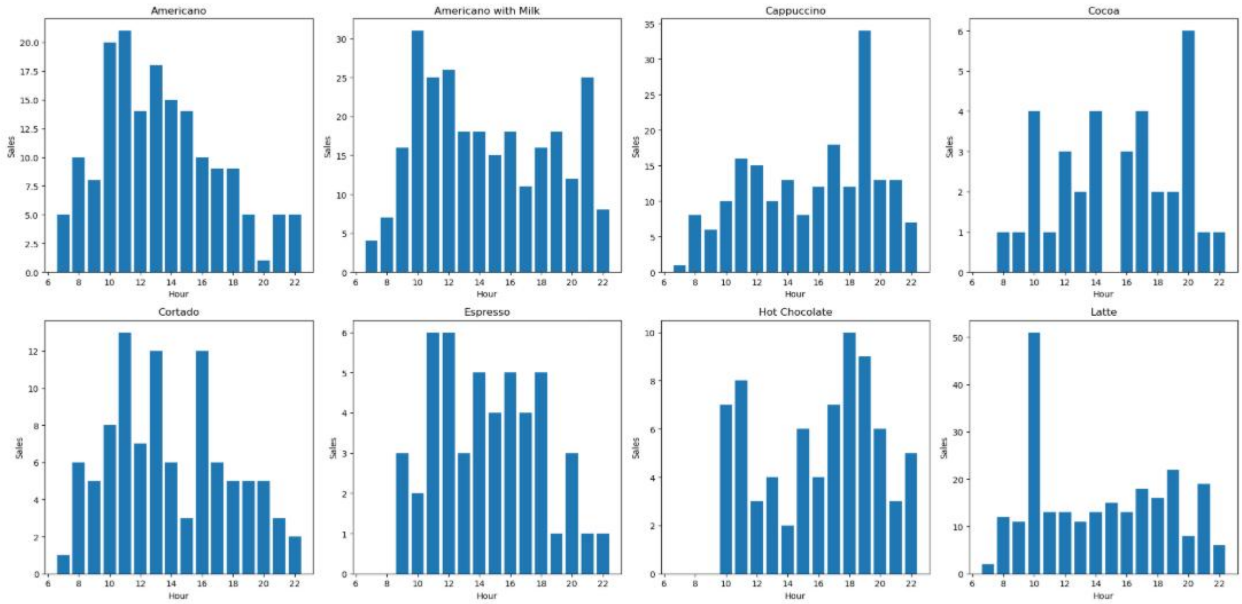
Sales Trends Over Time by Coffee Type

1) Hourly sales by coffee type

```
hourly_sales_coffee = coffee_data.pivot_table(
    index='hour',
    columns='coffee_name',
    values='transaction_date',
    aggfunc='count',
    fill_value=0
).reset_index()

hourly_sales_coffee
```

coffee_name	hour	Americano	Americano with Milk	Cappuccino	Cocoa	Cortado	Espresso	Hot Chocolate	Latte
0	7	5	4	1	0	1	0	0	2
1	8	10	7	8	1	6	0	0	12
2	9	8	16	6	1	5	3	0	11
3	10	20	31	10	4	8	2	7	51
4	11	21	25	16	1	13	6	8	13
5	12	14	26	15	3	7	6	3	13
6	13	18	18	10	2	12	3	4	11
7	14	15	18	13	4	6	5	2	13
8	15	14	15	8	0	3	4	6	15
9	16	10	18	12	3	12	5	4	13
10	17	9	11	18	4	6	4	7	18
11	18	9	16	12	2	5	5	10	16
12	19	5	18	34	2	5	1	9	22
13	20	1	12	13	6	5	3	6	8
14	21	5	25	13	1	3	1	3	19
15	22	5	8	7	1	2	1	5	6

```
#Hourly Sales by Coffee Type
fig, axs = plt.subplots(2, 4, figsize=(20, 10))

axs = axs.flatten()

for i, column in enumerate(hourly_sales_coffee.columns[1:]):

 axs[i].bar(hourly_sales_coffee['hour'],
 hourly_sales_coffee[column])
 axs[i].set_title(f'{column}')
 axs[i].set_xlabel('Hour')
 axs[i].set_ylabel('Sales')
plt.tight_layout()

plt.show()
```



Insights:

Sales are very low in the early morning (7–8 AM) and increase steadily after 9 AM. The highest activity is observed between 10 AM and 7 PM, which is the main peak period.

Latte shows the strongest demand, especially at 10 AM (51 sales) and remains high throughout the day.

Cappuccino peaks in the evening around 7 PM (34 sales), indicating higher preference for milk-based drinks later in the day.

Americano with Milk performs consistently well during late morning and evening hours.

Espresso remains the least preferred drink across all hours.

This indicates that customers prefer milk-based and premium drinks during working hours and evening time rather than early mornings.

```python
# Product Performance by Time
print("\n PRODUCT PERFORMANCE BY TIME PERIOD:")
morning = coffee_data[coffee_data['hour'].between(6, 11)]
afternoon = coffee_data[coffee_data['hour'].between(12, 17)]
evening = coffee_data[coffee_data['hour'].between(18, 23)]

print("\n  Morning (6AM-11AM) Top Product:", morning['coffee_name'].mode()[0])
print("  Afternoon (12PM-5PM) Top Product:", afternoon['coffee_name'].mode()[0])
print("  Evening (6PM-11PM) Top Product:", evening['coffee_name'].mode()[0])
```

```
PRODUCT PERFORMANCE BY TIME PERIOD:

 Morning (6AM-11AM) Top Product: Latte
 Afternoon (12PM-5PM) Top Product: Americano with Milk
 Evening (6PM-11PM) Top Product: Americano with Milk
```

```python
#Minimum and Maximum Hourly Sales of Coffee Types
hourly_sales_coffee.iloc[:,1:].describe().T.loc[:,['min','max']]
```

coffee_name	min	max
Americano	1.0	21.0
Americano with Milk	4.0	31.0
Cappuccino	1.0	34.0
Cocoa	1.0	6.0
Cortado	1.0	13.0
Espresso	1.0	6.0
Hot Chocolate	2.0	10.0
Latte	2.0	51.0

Insights:

Latte has the highest maximum sales (51), showing it is the most popular drink. Cappuccino (34) and Americano with Milk (31) also perform well. Espresso, Cocoa, and Hot Chocolate have much lower maximum sales, meaning they are less preferred compared to other coffee types.

```python
# Which coffee type sold out most in each hour?

coffee_columns = hourly_sales_coffee.columns.drop('hour')
hourly_sales_coffee[coffee_columns] = hourly_sales_coffee[coffee_columns].apply(pd.to_numeric, errors='coerce')


hourly_sales_coffee['top_coffee'] = hourly_sales_coffee[coffee_columns].idxmax(axis=1)
hourly_sales_coffee['top_sales'] = hourly_sales_coffee[coffee_columns].max(axis=1)


print(hourly_sales_coffee[['hour', 'top_coffee', 'top_sales']])
```

```
coffee_name  hour          top_coffee  top_sales
0               7           Americano        5.0
1               8               Latte       12.0
2               9  Americano with Milk       16.0
3              10               Latte       51.0
4              11  Americano with Milk       25.0
5              12  Americano with Milk       26.0
6              13           Americano       18.0
7              14  Americano with Milk       18.0
8              15  Americano with Milk       15.0
9              16  Americano with Milk       18.0
10             17          Cappuccino       18.0
11             18  Americano with Milk       16.0
12             19          Cappuccino       34.0
13             20          Cappuccino       13.0
14             21  Americano with Milk       25.0
15             22  Americano with Milk        8.0
```

Insights:

Morning (7–10 AM): Customers mostly prefer Latte and Americano with Milk.

Afternoon (11 AM – 4 PM): Americano with Milk dominates sales almost every hour.

Evening (5 PM – 10 PM): Customers shift towards Cappuccino, especially at 7–8 PM, where it records the highest evening sales.

Overall, Americano with Milk is the most consistent top-selling coffee throughout the day.

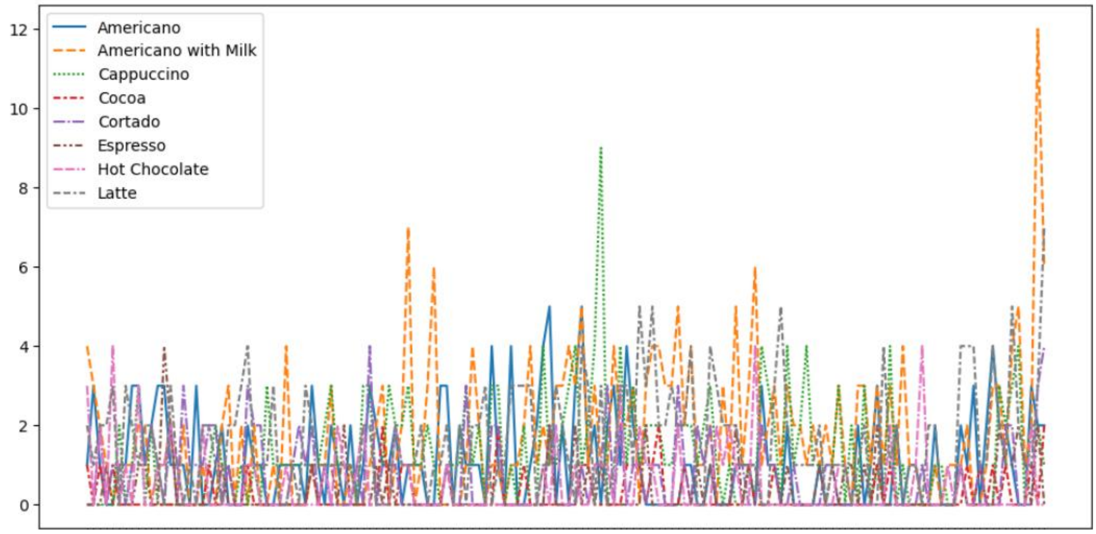
2) Daily sales by coffee type

```python
daily_sales_coffee = (
    coffee_data.groupby(['transaction_date', 'coffee_name'])
    .size()
    .reset_index(name='count')
    .pivot(index='transaction_date', columns='coffee_name', values='count')
    .fillna(0)
    .reset_index()
)

daily_sales_coffee
```

coffee_name	transaction_date	Americano	Americano with Milk	Cappuccino	Cocoa	Cortado	Espresso	Hot Chocolate	Latte
0	2024-03-01	1.0	4.0	0.0	1.0	0.0	0.0	3.0	2.0
1	2024-03-02	3.0	3.0	0.0	0.0	0.0	0.0	0.0	1.0
2	2024-03-03	1.0	2.0	0.0	1.0	2.0	0.0	2.0	2.0
3	2024-03-04	0.0	1.0	0.0	0.0	0.0	1.0	0.0	2.0
4	2024-03-05	0.0	0.0	0.0	1.0	1.0	0.0	4.0	3.0
...	...	...	...	...	...	...	...	...	...
145	2024-07-27	0.0	5.0	4.0	0.0	0.0	2.0	0.0	2.0
146	2024-07-28	0.0	1.0	0.0	0.0	0.0	1.0	0.0	1.0
147	2024-07-29	3.0	2.0	2.0	1.0	0.0	0.0	2.0	1.0
148	2024-07-30	2.0	12.0	2.0	0.0	3.0	2.0	0.0	3.0
149	2024-07-31	2.0	6.0	1.0	2.0	4.0	0.0	0.0	7.0

150 rows × 9 columns

```python
#Daily Sales by Coffee Type
plt.figure(figsize=(12,6))
sns.lineplot(data=daily_sales_coffee)
plt.legend(loc='upper left')
plt.xticks(range(len(daily_sales_coffee['transaction_date'])),daily_sales_coffee['transaction_date'],size='small')
plt.show()
```



```python
#Minimum and Maximum Datewise/Daily Sales of Coffee Types
daily_sales_coffee.iloc[:,1:].describe().T.loc[:,['min','max']]
```

	min	max
coffee_name		
Americano	0.0	5.0
Americano with Milk	0.0	12.0
Cappuccino	0.0	9.0
Cocoa	0.0	2.0
Cortado	0.0	4.0
Espresso	0.0	4.0
Hot Chocolate	0.0	4.0
Latte	0.0	7.0

Insights:

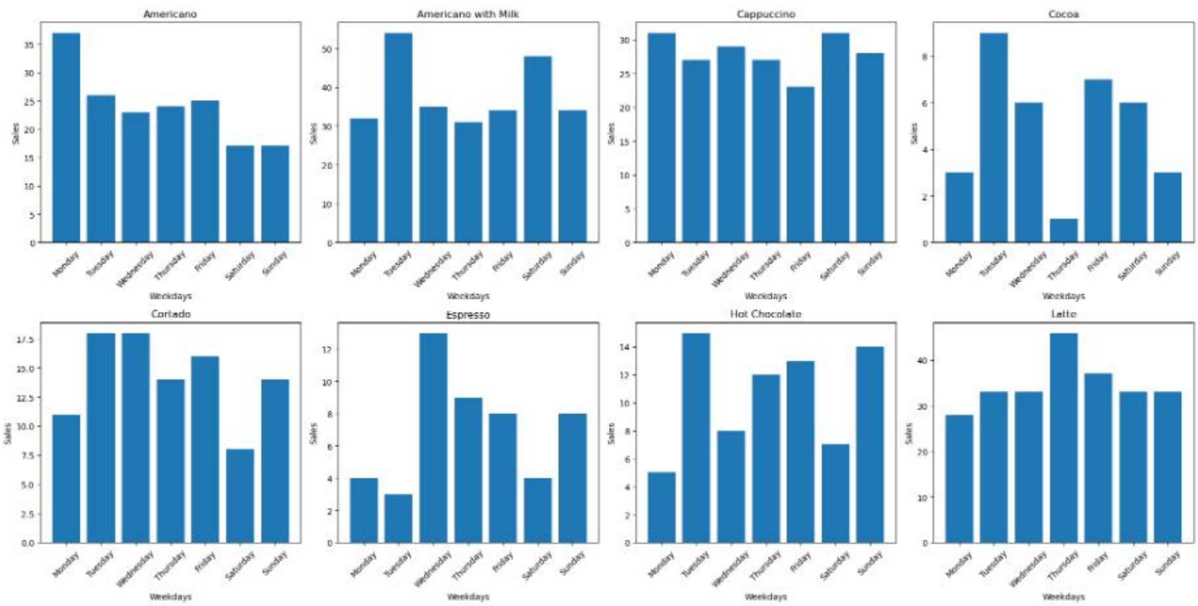
On some days, all coffee types record zero sales, showing that not every product sells daily. The highest daily sales are seen for Americano with Milk (12), Cappuccino (9) and Latte (7), making them the strongest daily performers, while Cocoa, Espresso, Cortado, and Hot Chocolate have very low maximum daily sales, indicating low demand.

3) Weekday sales by coffee type

weekday_sales_coffee
=coffee_data.groupby(['coffee_name','day_name']).count()['transaction_date'].reset_index().rename(columns={'transaction_date':'count'}).pivot(index='day_name',columns='coffee_name',values='count').reset_index()
weekday_sales_coffee

coffee_name	day_name	Americano	Americano with Milk	Cappuccino	Cocoa	Cortado	Espresso	Hot Chocolate	Latte
0	Friday	25	34	23	7	16	8	13	37
1	Monday	37	32	31	3	11	4	5	28
2	Saturday	17	48	31	6	8	4	7	33
3	Sunday	17	34	28	3	14	8	14	33
4	Thursday	24	31	27	1	14	9	12	46
5	Tuesday	26	54	27	9	18	3	15	33
6	Wednesday	23	35	29	6	18	13	8	33

```
#Weekday Sales by Coffee Type

weekday_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']


weekday_sales_coffee = weekday_sales_coffee.set_index('day_name').loc[weekday_order].reset_index()

fig, axs = plt.subplots(2, 4, figsize=(20, 10))
axs = axs.flatten()

for i, column in enumerate(weekday_sales_coffee.columns[1:]):
    axs[i].bar(weekday_sales_coffee['day_name'], weekday_sales_coffee[column])
    axs[i].set_title(f'{column}')
    axs[i].set_xlabel('Weekdays')
    axs[i].set_ylabel('Sales')


    axs[i].tick_params(axis='x', rotation=45)

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



Insights:

Latte is the top-selling coffee on most weekdays, especially on Thursday (46 sales).

Americano with Milk performs very well on Tuesday (54 sales) and Saturday (48 sales).

Cappuccino has consistent sales across all days, usually between 27–31.

Espresso, Cocoa, and Cortado have the lowest sales on all days, showing lower demand.

Overall, Latte and Americano with Milk are the most popular coffee types, while simpler or smaller drinks sell less consistently.

```
#Minimum and Maximum Weekdays Sales of Coffee Types
weekday_sales_coffee.iloc[:,1:].describe().T.loc[:,['min','max']]
```

coffee_name	min	max
Americano	17.0	37.0
Americano with Milk	31.0	54.0
Cappuccino	23.0	31.0
Cocoa	1.0	9.0
Cortado	8.0	18.0
Espresso	3.0	13.0
Hot Chocolate	5.0	15.0
Latte	28.0	46.0

```
# Which coffee type sold out most in each weekday?

coffee_columns = weekday_sales_coffee.columns.drop('day_name')
weekday_sales_coffee[coffee_columns] = weekday_sales_coffee[coffee_columns].apply(pd.to_numeric, errors='coerce')


weekday_sales_coffee['top_coffee'] = weekday_sales_coffee[coffee_columns].idxmax(axis=1)
weekday_sales_coffee['top_sales'] = weekday_sales_coffee[coffee_columns].max(axis=1)


print(weekday_sales_coffee[['day_name', 'top_coffee', 'top_sales']])
```

```
coffee_name   day_name           top_coffee  top_sales
0               Friday                Latte         37
1               Monday            Americano         37
2             Saturday  Americano with Milk         48
3               Sunday  Americano with Milk         34
4             Thursday                Latte         46
5              Tuesday  Americano with Milk         54
6            Wednesday  Americano with Milk         35
```

Insights:

Americano with Milk has the highest weekday sales, ranging from 31 to 54, making it the most consistent top performer.

Latte also sells very well, with sales between 28 and 46.

Cappuccino has steady sales (23–31) across the week.

Espresso, Cocoa, Cortado, and Hot Chocolate sell much less, showing lower demand.

Latte is the top-selling coffee on Friday and Thursday.

Americano with Milk dominates on Tuesday, Wednesday, Saturday, and Sunday.

Americano is the top seller only on Monday.

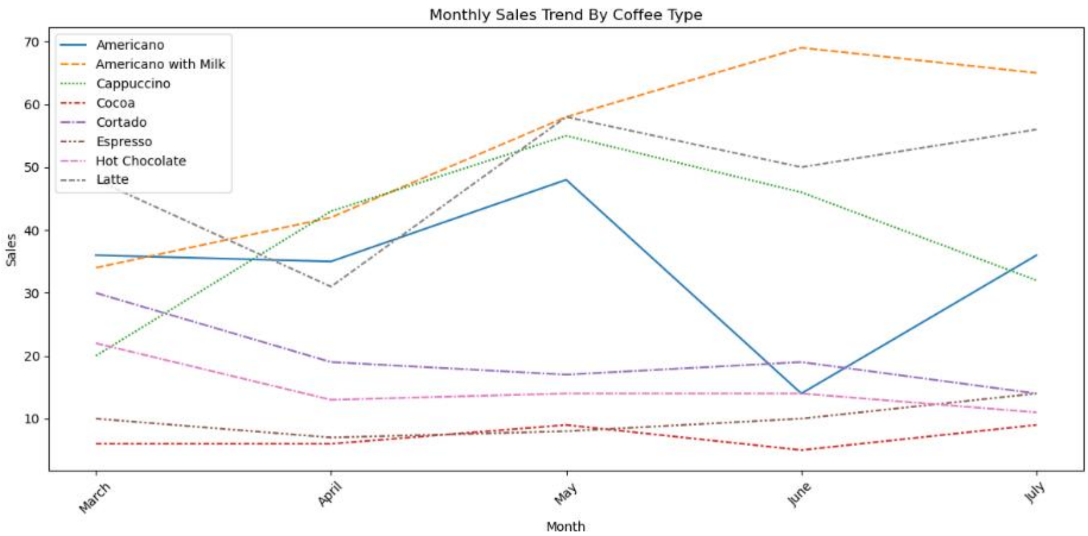
Overall, Americano with Milk and Latte are the most popular coffees across the weekdays.

4) Monthly sales by coffee type

monthly_sales_coffee =coffee_data.groupby(['coffee_name','month_name']).count()['transaction_date'].reset_index().rename(columns={'transaction_date':'count'}).pivot(index='month_name',columns='coffee_name',values='count').reset_index()
monthly_sales_coffee

coffee_name	month_name	Americano	Americano with Milk	Cappuccino	Cocoa	Cortado	Espresso	Hot Chocolate	Latte
0	April	35	42	43	6	19	7	13	31
1	July	36	65	32	9	14	14	11	56
2	June	14	69	46	5	19	10	14	50
3	March	36	34	20	6	30	10	22	48
4	May	48	58	55	9	17	8	14	58

```
#Monthly Sales by Coffee Type
month_order = ['March', 'April', 'May', 'June', 'July']
monthly_sales_coffee = (monthly_sales_coffee.set_index('month_name').loc[month_order].reset_index())
plt.figure(figsize=(12,6))

sns.lineplot(data=monthly_sales_coffee)

plt.legend(loc='upper left')
plt.xticks(
    range(len(monthly_sales_coffee['month_name'])),
    monthly_sales_coffee['month_name'],
    fontsize=10,
    rotation=45
)

plt.xlabel("Month")
plt.ylabel("Sales")
plt.title("Monthly Sales Trend By Coffee Type")
plt.tight_layout()
plt.show()
```



Insights:

Latte consistently sells well across all months, with the highest in May (58) and July (56).

Americano with Milk is the top seller in June (69) and July (65), showing strong popularity.

Cappuccino performs steadily, peaking in May (55).

Americano has moderate sales, while Espresso, Cocoa, Cortado, and Hot Chocolate sell the least.

Overall, Latte and Americano with Milk are the strongest performers every month, while simpler or smaller drinks have lower sales.

```
#Minimum and Maximum Monthly Sales of Coffee Types
monthly_sales_coffee.iloc[:,1:].describe().T.loc[:,['min','max']]
```

coffee_name	min	max
Americano	14.0	48.0
Americano with Milk	34.0	69.0
Cappuccino	20.0	55.0
Cocoa	5.0	9.0
Cortado	14.0	30.0
Espresso	7.0	14.0
Hot Chocolate	11.0	22.0
Latte	31.0	58.0

Insights:
Americano with Milk has the highest monthly sales, ranging from 34 to 69, making it the most popular coffee each month.

Latte also sells very well, between 31 and 58.

Cappuccino has steady monthly sales (20–55).

Espresso, Cocoa, Cortado, and Hot Chocolate have lower sales, showing less demand.

Overall, Americano with Milk and Latte are the top-selling coffees every month.

```
# Which coffee type sold out most in each month?

monthly_sales_coffee = (
    coffee_data.groupby(['month_name', 'coffee_name'])
    .size()
    .reset_index(name='count')
    .pivot(index='month_name', columns='coffee_name', values='count')
    .fillna(0)
    .reset_index()
)


coffee_columns = monthly_sales_coffee.columns.drop('month_name')
monthly_sales_coffee[coffee_columns] = monthly_sales_coffee[coffee_columns].apply(pd.to_numeric, errors='coerce')


monthly_sales_coffee['top_coffee'] = monthly_sales_coffee[coffee_columns].idxmax(axis=1)
monthly_sales_coffee['top_sales'] = monthly_sales_coffee[coffee_columns].max(axis=1)


print(monthly_sales_coffee[['month_name', 'top_coffee', 'top_sales']])
```

```
coffee_name month_name          top_coffee  top_sales
0                April          Cappuccino         43
1                 July  Americano with Milk         65
2                 June  Americano with Milk         69
3                March               Latte         48
4                  May  Americano with Milk         58
```

Insights:
Americano with Milk is the top-selling coffee in May, June, and July.

Latte is the top seller in March.

Cappuccino leads in April.

Overall, Americano with Milk dominates most months, while Latte and Cappuccino occasionally take the top spot.

Revenue Trends Over Time By Coffee Type

1) Hourly Revenue by coffee type

```
#Hourly Revenue by coffee type
hourly_revenue_coffee = (
    coffee_data.groupby(['hour', 'coffee_name'])['transaction_amount']
    .sum()
    .reset_index()
    .pivot(index='hour', columns='coffee_name', values='transaction_amount')
    .fillna(0)
    .reset_index()
)

hourly_revenue_coffee
```

coffee_name	hour	Americano	Americano with Milk	Cappuccino	Cocoa	Cortado	Espresso	Hot Chocolate	Latte
0	7	137.86	123.66	32.82	0.00	27.92	0.00	0.00	70.54
1	8	254.70	215.04	296.86	32.82	157.72	0.00	0.00	423.24
2	9	199.94	482.20	201.82	39.00	129.80	60.24	0.00	402.48
3	10	558.52	992.16	378.82	146.96	223.48	48.02	257.18	1948.04
4	11	560.08	784.68	595.32	37.72	366.02	124.40	296.20	494.22
5	12	395.88	835.14	563.84	114.14	204.50	138.16	115.12	483.82
6	13	510.40	586.84	387.64	71.52	337.00	71.02	154.80	392.38
7	14	423.90	590.96	496.24	141.08	170.46	107.26	71.52	483.50
8	15	400.02	488.60	300.12	0.00	86.82	94.04	232.84	556.32
9	16	282.14	581.16	458.18	116.42	336.02	118.04	151.86	481.54
10	17	253.36	356.34	674.00	154.12	166.54	94.04	270.24	670.44
11	18	253.24	533.16	450.68	77.40	141.56	115.10	383.08	603.82
12	19	136.78	585.86	1264.18	76.42	137.64	25.00	340.78	821.66
13	20	27.92	374.24	486.74	222.70	129.80	64.16	221.42	292.94
14	21	120.00	817.96	490.36	32.82	78.86	18.12	108.26	677.48
15	22	129.80	253.94	255.52	32.82	50.94	23.02	175.18	206.72

Insights:

Revenue is low in the early morning (7–8 AM) and increases significantly after 9 AM, peaking around 10–11 AM.

Latte generates the highest revenue at 10 AM (1948 dollars), making it the most profitable coffee during peak hours.

Americano with Milk also brings high revenue in late morning and afternoon hours, especially at 10–12 PM.

Cappuccino has steady revenue throughout the day, peaking at 7 PM (674 dollars).

Espresso, Cocoa, Cortado, and Hot Chocolate contribute less to total revenue.

Overall, Latte and Americano with Milk drive most of the hourly revenue, while smaller or simpler drinks have a minor impact.

```
# Which coffee type generated more revenue in each hour?
coffee_columns = hourly_revenue_coffee.columns.drop('hour')
hourly_revenue_coffee['top_coffee'] = hourly_revenue_coffee[coffee_columns].idxmax(axis=1)
hourly_revenue_coffee['top_revenue'] = hourly_revenue_coffee[coffee_columns].max(axis=1)

print(hourly_revenue_coffee[['hour', 'top_coffee', 'top_revenue']])
```

```
coffee_name  hour          top_coffee  top_revenue
0               7           Americano       137.86
1               8               Latte       423.24
2               9  Americano with Milk      482.20
3              10               Latte      1948.04
4              11  Americano with Milk      784.68
5              12  Americano with Milk      835.14
6              13  Americano with Milk      586.84
7              14  Americano with Milk      590.96
8              15               Latte       556.32
9              16  Americano with Milk      581.16
10             17          Cappuccino       674.00
11             18               Latte       603.82
12             19          Cappuccino      1264.18
13             20          Cappuccino       486.74
14             21  Americano with Milk      817.96
15             22          Cappuccino       255.52
```

Insights:

Latte generates the most revenue in the morning peak hours (8 AM, 10 AM, 3 PM, 6 PM).

Americano with Milk dominates revenue in late morning and afternoon (9 AM, 11 AM–4 PM, 9 PM).

Cappuccino takes the top spot in the evening (5 PM, 7 PM, 8 PM, 10 PM).

Americano leads only at 7 AM, early in the day.

Overall, Latte and Americano with Milk are the main revenue drivers, while Cappuccino contributes strongly in the evening.

```
#Minimum and Maximum Hourly Revenue generation by coffee types
hourly_revenue_coffee.iloc[:,1:].describe().T.loc[:,['min','max']]
```

coffee_name	min	max
Americano	27.92	560.08
Americano with Milk	123.66	992.16
Cappuccino	32.82	1264.18
Cocoa	0.00	222.70
Cortado	27.92	366.02
Espresso	0.00	138.16
Hot Chocolate	0.00	383.08
Latte	70.54	1948.04
top_revenue	137.86	1948.04

Insights:

Latte generates the highest hourly revenue, ranging from 70 to 1948 dollars, making it the most profitable coffee.

Cappuccino and Americano with Milk also bring high revenue, with maximums of 1264 and 992 dollars respectively.

Americano has moderate revenue (28–560 dollars), while Espresso, Cocoa, Cortado, and Hot Chocolate earn much less.

Overall, Latte, Cappuccino, and Americano with Milk are the main revenue drivers, while other coffees contribute less.

2) Daily revenue by coffee type

```
#Daily Revenue by coffee type
daily_revenue_coffee = (
    coffee_data.groupby(['transaction_date', 'coffee_name'])['transaction_amount']
    .sum()
    .reset_index()
    .pivot(index='transaction_date', columns='coffee_name', values='transaction_amount')
    .fillna(0)
    .reset_index()
)

coffee_columns = daily_revenue_coffee.columns.drop('transaction_date')
daily_revenue_coffee['top_coffee'] = daily_revenue_coffee[coffee_columns].idxmax(axis=1)
daily_revenue_coffee['top_revenue'] = daily_revenue_coffee[coffee_columns].max(axis=1)

print(daily_revenue_coffee[['transaction_date', 'top_coffee', 'top_revenue']])
```

```
coffee_name transaction_date          top_coffee  top_revenue
0                 2024-03-01  Americano with Milk       135.20
1                 2024-03-02  Americano with Milk       101.40
2                 2024-03-03                Latte        78.70
3                 2024-03-04                Latte        77.40
4                 2024-03-05        Hot Chocolate       154.80
..                       ...                  ...          ...
145               2024-07-27  Americano with Milk       139.60
146               2024-07-28                Latte        32.82
147               2024-07-29            Americano        69.06
148               2024-07-30  Americano with Milk       335.04
149               2024-07-31                Latte       229.74

[150 rows x 3 columns]
```

```
#Minimum and Maximum Daily Revenue generation by coffee types
daily_revenue_coffee.iloc[:,1:].describe().T.loc[:,['min','max']]
```

coffee_name	min	max
Americano	0.00	140.68
Americano with Milk	0.00	335.04
Cappuccino	0.00	339.48
Cocoa	0.00	77.40
Cortado	0.00	117.80
Espresso	0.00	97.00
Hot Chocolate	0.00	154.80
Latte	0.00	229.74
top_revenue	27.92	339.48

Insights:
Cappuccino and Americano with Milk generate the highest daily revenue, with maximums of 339.48 and 335.04 dollars respectively.

Latte also earns well, up to 229.74 dollars per day.

Americano, Espresso, Cocoa, Cortado, and Hot Chocolate have lower daily revenue, often close to zero on some days.

Overall, Americano with Milk, Cappuccino, and Latte are the main contributors to daily revenue.

3) Weekday revenue by coffee type

```
#Weekdays Revenue by coffee type
weekday_revenue_coffee = (
    coffee_data.groupby(['day_name', 'coffee_name'])['transaction_amount']
    .sum()
    .reset_index()
    .pivot(index='day_name', columns='coffee_name', values='transaction_amount')
    .fillna(0)
    .reset_index()
)

#Which coffee type created more revenue in each weekday?
coffee_columns = weekday_revenue_coffee.columns.drop('day_name')
weekday_revenue_coffee['top_coffee'] = weekday_revenue_coffee[coffee_columns].idxmax(axis=1)
weekday_revenue_coffee['top_revenue'] = weekday_revenue_coffee[coffee_columns].max(axis=1)

print(weekday_revenue_coffee[['day_name', 'top_coffee', 'top_revenue']])
```

```
coffee_name   day_name          top_coffee  top_revenue
0               Friday               Latte      1366.80
1               Monday          Cappuccino      1165.36
2             Saturday  Americano with Milk     1563.82
3               Sunday               Latte      1236.56
4             Thursday               Latte      1727.20
5              Tuesday  Americano with Milk     1682.74
6            Wednesday               Latte      1203.56
```

```
##Minimum and Maximum Weekday Revenue generation by coffee types
weekday_revenue_coffee.iloc[:,1:].describe().T.loc[:,['min','max']]
```

coffee_name	min	max
Americano	471.90	1013.96
Americano with Milk	1007.62	1682.74
Cappuccino	864.60	1165.36
Cocoa	32.82	339.78
Cortado	228.26	496.80
Espresso	59.26	298.32
Hot Chocolate	179.78	572.00
Latte	1046.98	1727.20
top_revenue	1165.36	1727.20

Insights:

Latte generates the highest revenue on Friday, Sunday, Thursday, and Wednesday, with a maximum of 1727.20 dollars on Thursday.

Americano with Milk tops revenue on Tuesday and Saturday, reaching up to 1682.74 dollars.

Cappuccino leads only on Monday.

Americano, Espresso, Cocoa, Cortado, and Hot Chocolate earn much less revenue on weekdays.

Overall, Latte and Americano with Milk are the main weekday revenue drivers, while other coffees contribute significantly less.

5) Monthly revenue by coffee type

```
#Monthly  Revenue generation by coffee types
monthly_revenue_coffee = (
    coffee_data.groupby(['month_name', 'coffee_name'])['transaction_amount']
    .sum()
    .reset_index()
    .pivot(index='month_name', columns='coffee_name', values='transaction_amount')
    .fillna(0)
    .reset_index()
)
#Which coffee type created more revenue in each month?
coffee_columns = monthly_revenue_coffee.columns.drop('month_name')
monthly_revenue_coffee['top_coffee'] = monthly_revenue_coffee[coffee_columns].idxmax(axis=1)
monthly_revenue_coffee['top_revenue'] = monthly_revenue_coffee[coffee_columns].max(axis=1)

print(monthly_revenue_coffee[['month_name', 'top_coffee', 'top_revenue']])
```

```
coffee_name month_name          top_coffee  top_revenue
0                April          Cappuccino      1659.44
1                 July  Americano with Milk     1863.80
2                 June  Americano with Milk     2268.12
3                March               Latte      1874.50
4                  May               Latte      2198.00
```

```
#Minimum and Maximum Monthly Revenue generation by coffee types
monthly_revenue_coffee.iloc[:,1:].describe().T.loc[:,['min','max']]
```

coffee_name	min	max
Americano	390.88	1348.80
Americano with Milk	1154.00	2268.12
Cappuccino	780.50	2078.44
Cocoa	189.88	340.76
Cortado	322.28	869.20
Espresso	171.00	273.28
Hot Chocolate	361.02	854.00
Latte	1193.12	2198.00
top_revenue	1659.44	2268.12

Insights:

Americano with Milk generates the highest revenue in June (2268.12 dollars) and July (1863.80 dollars).

Latte leads in March (1874.50 dollars) and May (2198.00 dollars).

Cappuccino tops revenue only in April (1659.44 dollars).

Americano, Espresso, Cocoa, Cortado, and Hot Chocolate earn much less compared to these top three.

Overall, Americano with Milk and Latte are the main revenue drivers each month, while Cappuccino occasionally leads, and other coffees contribute less.

Customer Purchase Behaviour Analysis

```
coffee_data['card'].value_counts()
```

```
CASH_USER              89
ANON-0000-0000-0012    88
ANON-0000-0000-0009    63
ANON-0000-0000-0097    27
ANON-0000-0000-0003    23
                       ..
ANON-0000-0000-0196     1
ANON-0000-0000-0195     1
ANON-0000-0000-0193     1
ANON-0000-0000-0190     1
ANON-0000-0000-0446     1
Name: card, Length: 447, dtype: int64
```

There are 89 purchases made using cash. These may come from one or multiple customers, but we cannot identify them individually because cash user IDs are not available. Only the card users' customer IDs are known, so analysis of unique cash customers is not possible.

```
# Customer Behavior (Card users only)
card_customers = coffee_data[coffee_data['payment_type'] == 'card'].groupby('card').size().sort_values(ascending=False)
print(f"\n CUSTOMER INSIGHTS (Card Users):")
print(f"  • Total Unique Customers: {len(card_customers)}")
print(f"  • Average Purchases per Customer: {card_customers.mean():.1f}")
print(f"  • Purchase Count of Most Frequent Customer: {card_customers.iloc[0]} purchases")
```

```
 CUSTOMER INSIGHTS (Card Users):
  • Total Unique Customers: 446
  • Average Purchases per Customer: 2.3
  • Purchase Count of Most Frequent Customer: 88 purchases
```

```
# Filter out CASH_USER
card_customers = coffee_data[coffee_data['card'] != 'CASH_USER']

# Count transactions per card customer
top_card_customers = (
    card_customers['card']
    .value_counts()
    .head(10)
    .reset_index()
    .rename(columns={'index': 'customer_id', 'card': 'purchase_count'})
)

print(top_card_customers)
```

```
           customer_id  purchase_count
0  ANON-0000-0000-0012              88
1  ANON-0000-0000-0009              63
2  ANON-0000-0000-0097              27
3  ANON-0000-0000-0003              23
4  ANON-0000-0000-0040              22
5  ANON-0000-0000-0001              17
6  ANON-0000-0000-0141              17
7  ANON-0000-0000-0059              12
8  ANON-0000-0000-0024              12
9  ANON-0000-0000-0180              12
```

Insights:

These are the transaction details of the top 10 card users by purchase frequency after filtering out cash users.

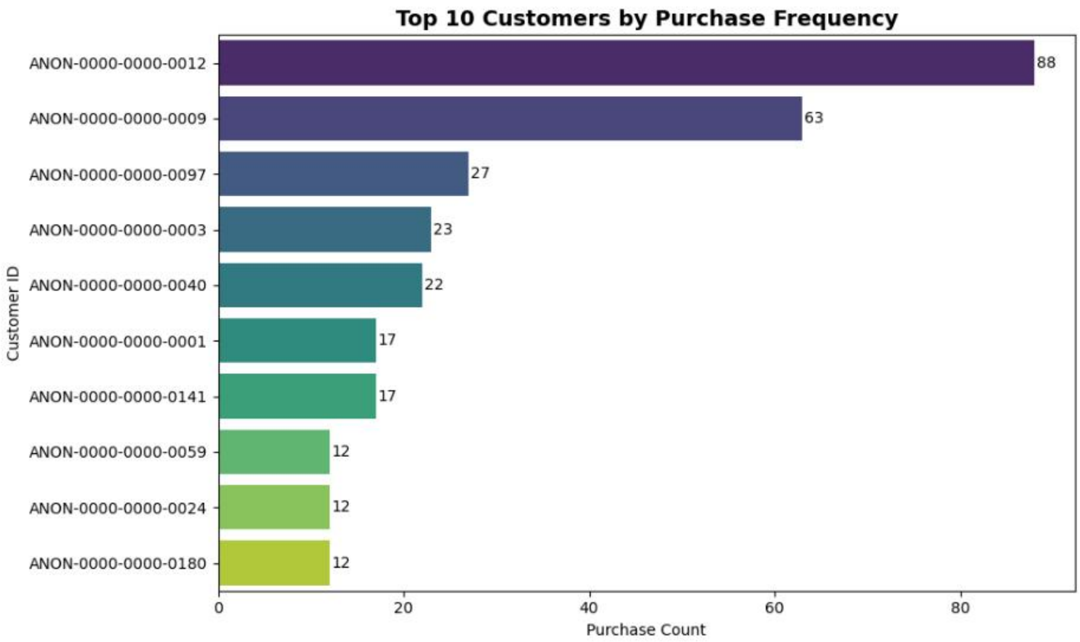
The top 10 card customers account for a significant number of purchases.

The most frequent card customer, ANON-0000-0000-0012, made 88 purchases, followed by ANON-0000-0000-0009 with 63 purchases.

Other top customers made between 12–27 purchases each.

Overall, a small group of loyal card customers contributes heavily to sales, highlighting the importance of targeting and retaining these frequent buyers.

```
#Top 10 Customers by Purchase Frequency( Card Customers). These are the frequent customers
plt.figure(figsize=(10,6))
ax = sns.barplot(
   data=top_card_customers,
   x='purchase_count',
   y='customer_id',
   palette='viridis'
)

plt.title("Top 10 Customers by Purchase Frequency", fontsize=14, fontweight='bold')
plt.xlabel("Purchase Count")
plt.ylabel("Customer ID")


for p in ax.patches:
   width = p.get_width()
   ax.text(
      width + 0.2,
      p.get_y() + p.get_height() / 2,
      f"{width:.0f}",
      va='center'
   )

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



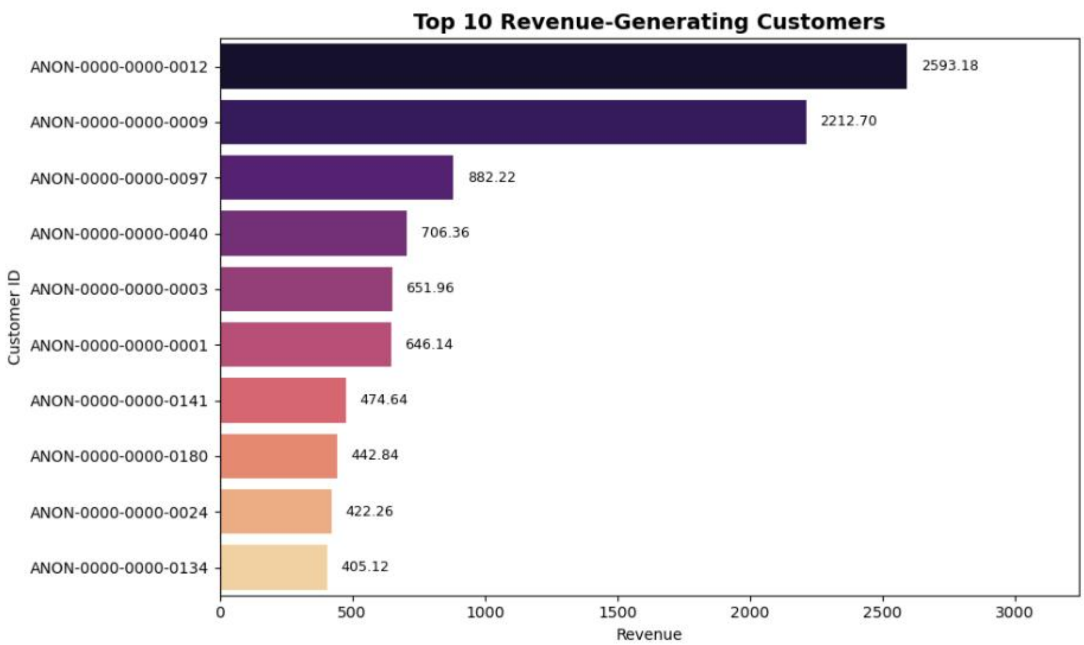

```
#Top revenue generating card customers
card_customers = coffee_data[coffee_data['card'] != 'CASH_USER']


top_revenue_customers = (
    card_customers.groupby('card')['transaction_amount']
    .sum()
    .sort_values(ascending=False)
    .head(10)
    .reset_index()
    .rename(columns={'card': 'customer_id', 'transaction_amount': 'revenue'})
)
print(top_revenue_customers)
```

```
           customer_id  revenue
0  ANON-0000-0000-0012  2593.18
1  ANON-0000-0000-0009  2212.70
2  ANON-0000-0000-0097   882.22
3  ANON-0000-0000-0040   706.36
4  ANON-0000-0000-0003   651.96
5  ANON-0000-0000-0001   646.14
6  ANON-0000-0000-0141   474.64
7  ANON-0000-0000-0180   442.84
8  ANON-0000-0000-0024   422.26
9  ANON-0000-0000-0134   405.12
```

#Top 10 Revenue-Generating card Customers

```
plt.figure(figsize=(10,6))
ax = sns.barplot(
    data=top_revenue_customers,
    x='revenue',
    y='customer_id',
    palette='magma'
)

plt.title("Top 10 Revenue-Generating Customers", fontsize=14, fontweight='bold')
plt.xlabel("Revenue")
plt.ylabel("Customer ID")
```

```
max_val = top_revenue_customers['revenue'].max()
plt.xlim(0, max_val * 1.25)


for p in ax.patches:
    width = p.get_width()
    ax.text(
        width + (max_val * 0.02),
        p.get_y() + p.get_height() / 2,
        f"{width:.2f}",
        ha='left',
        va='center',
        fontsize=9
    )

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



Insights:

The top 10 card customers generate a large portion of revenue.

The highest revenue comes from ANON-0000-0000-0012 (2593.18 dollars), followed by ANON-0000-0000-0009 (2212.70 dollars).

Other top customers bring between 405–882 dollars each.

Overall, a small group of loyal card customers contributes significantly to total revenue, making them key for retention and marketing efforts.

```python
# Preferred Coffee type of most frequent customers
card_customers = coffee_data[coffee_data['card'] != 'CASH_USER']


top_card_customers = (
    card_customers['card']
    .value_counts()
    .head(10)
    .reset_index()
    .rename(columns={'index': 'customer_id', 'card': 'purchase_count'})
)

top10_ids = top_card_customers['customer_id']
top10_data = card_customers[card_customers['card'].isin(top10_ids)]
preferred_coffee_each = (
    top10_data.groupby('card')['coffee_name']
    .agg(lambda x: x.value_counts().idxmax())
    .reset_index()
    .rename(columns={'card': 'customer_id', 'coffee_name': 'preferred_coffee'})
)
print(preferred_coffee_each)
```

```
           customer_id     preferred_coffee
0  ANON-0000-0000-0001                Latte
1  ANON-0000-0000-0003            Americano
2  ANON-0000-0000-0009                Latte
3  ANON-0000-0000-0012            Americano
4  ANON-0000-0000-0024  Americano with Milk
5  ANON-0000-0000-0040  Americano with Milk
6  ANON-0000-0000-0059  Americano with Milk
7  ANON-0000-0000-0097  Americano with Milk
8  ANON-0000-0000-0141              Cortado
9  ANON-0000-0000-0180           Cappuccino
```

```python
top10_ids = top_card_customers['customer_id'].tolist()
top10_data = card_customers[card_customers['card'].isin(top10_ids)]
preferred_coffee = (
   top10_data.groupby(['card', 'coffee_name'])
   .size()
   .reset_index(name='count')
)
preferred_top = (
   preferred_coffee.loc[
      preferred_coffee.groupby('card')['count'].idxmax()
   ]
)
final_preference = top_card_customers.merge(
   preferred_top,
   left_on='customer_id',
   right_on='card',
   how='left'
).drop(columns=['card'])
final_preference = final_preference.rename(
   columns={
      'purchase_count': 'total_purchases',
      'coffee_name': 'preferred_coffee',
      'count': 'preferred_coffee_purchases'
```

```
    }
)
print(final_preference)
```

```
           customer_id  total_purchases     preferred_coffee  \
0  ANON-0000-0000-0012               88            Americano
1  ANON-0000-0000-0009               63                Latte
2  ANON-0000-0000-0097               27  Americano with Milk
3  ANON-0000-0000-0003               23            Americano
4  ANON-0000-0000-0040               22  Americano with Milk
5  ANON-0000-0000-0001               17                Latte
6  ANON-0000-0000-0141               17              Cortado
7  ANON-0000-0000-0059               12  Americano with Milk
8  ANON-0000-0000-0024               12  Americano with Milk
9  ANON-0000-0000-0180               12           Cappuccino

   preferred_coffee_purchases
0                          40
1                          23
2                          21
3                          17
4                           8
5                          17
6                          16
7                           7
8                           8
9                          10
```

Insights:

Most frequent customers have clear coffee preferences.

ANON-0000-0000-0012 bought Americano the most (40 out of 88 purchases).

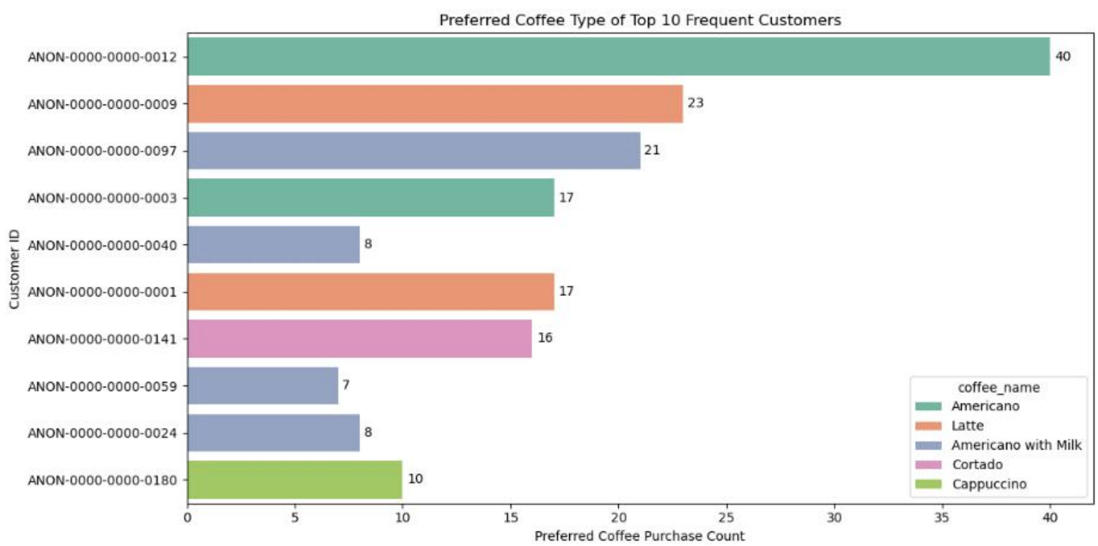
ANON-0000-0000-0009 prefers Latte, and ANON-0000-0000-0097 prefers Americano with Milk.

Many top customers repeatedly buy their favorite coffee, showing strong brand/product loyalty.

Overall, frequent customers tend to stick to one or two preferred coffee types, which can help in personalized marketing and promotions.

```
#Preferred Coffee Type of Top 10 Frequent Customers

print("Columns before rename:", final_preference.columns.tolist())


rename_map = {}

if 'purchase_count_x' in final_preference.columns:
    rename_map['purchase_count_x'] = 'total_purchase_count'

if 'purchase_count_y' in final_preference.columns:
    rename_map['purchase_count_y'] = 'coffee_purchase_count'
```

```
final_preference = final_preference.rename(columns=rename_map)


print("Columns after rename:", final_preference.columns.tolist())


plt.figure(figsize=(12, 6))

sns.barplot(
    data=final_preference,
    y='customer_id',
    x='coffee_purchase_count',
    hue='coffee_name',
    dodge=False,
    palette='Set2'
)


for index, row in final_preference.iterrows():
    plt.text(
        row['coffee_purchase_count'] + 0.2,
        index,
        f"{row['coffee_purchase_count']:.0f}",
        va='center'
    )

plt.xlabel("Preferred Coffee Purchase Count")
plt.ylabel("Customer ID")
plt.title("Preferred Coffee Type of Top 10 Frequent Customers")
plt.tight_layout()
plt.show()
```



```python
# Top Average Spend per customers
card_customers = coffee_data[coffee_data['card'] != 'CASH_USER']


avg_spend = (
    card_customers.groupby('card')['transaction_amount']
    .mean()
    .reset_index()
    .rename(columns={'card': 'customer_id', 'transaction_amount': 'avg_spend'})
)


top_10_avg_spenders = avg_spend.sort_values(by='avg_spend', ascending=False).head(10)


top_10_avg_spenders['avg_spend'] = top_10_avg_spenders['avg_spend'].round(2)

print(top_10_avg_spenders)
```

```
             customer_id  avg_spend
92  ANON-0000-0000-0093       38.7
54  ANON-0000-0000-0055       38.7
28  ANON-0000-0000-0029       38.7
29  ANON-0000-0000-0030       38.7
30  ANON-0000-0000-0031       38.7
87  ANON-0000-0000-0088       38.7
86  ANON-0000-0000-0087       38.7
33  ANON-0000-0000-0034       38.7
85  ANON-0000-0000-0086       38.7
35  ANON-0000-0000-0036       38.7
```

Insights:

The top 10 card customers spend the most on average per transaction, with each spending around 38.70 dollars.

These customers may not make the most purchases, but when they do, they buy higher-value items, making them very valuable.

Targeting these high average spenders with promotions or loyalty programs can help increase revenue.

```python
avg_spend_all = coffee_data['transaction_amount'].mean()
print("Average Spend of All Customers (including CASH_USER):", avg_spend_all)
card_customers = coffee_data[coffee_data['card'] != 'CASH_USER']
avg_spend_card = card_customers['transaction_amount'].mean()

print("Average Spend of Card Customers (excluding CASH_USER):", avg_spend_card)
cash_customers = coffee_data[coffee_data['card'] == 'CASH_USER']
avg_spend_cash = cash_customers['transaction_amount'].mean()

print("Average Spend of Cash Customers (CASH_USER only):", avg_spend_cash)
```

```
Average Spend of All Customers (including CASH_USER): 33.10580759046762
Average Spend of Card Customers (excluding CASH_USER): 32.87632183908031
Average Spend of Cash Customers (CASH_USER only): 35.79775280898876
```

Insights:

Since individual cash customers cannot be uniquely identified, the analysis compares average transaction values instead of average customer spend. The results show that cash transactions (35.79 dollars) have a higher average value than card transactions (32.87 dollars), indicating that customers paying with cash tend to make slightly higher-value purchases per visit. Average spend per transaction is higher for cash payments than card payments.

Limitations of Analysis:

- Cash customers cannot be uniquely identified.
- Customer-level behaviour analysis is limited to card users only.

```python
#  Top preferred coffee types by Cash User Customers
cash_users = coffee_data[coffee_data['card'] == 'CASH_USER']


cash_pref = (
    cash_users['coffee_name']
    .value_counts()
    .reset_index()
    .rename(columns={'index': 'coffee_name', 'coffee_name': 'purchase_count'})
)

print(cash_pref.head(10))
```

```
          coffee_name  purchase_count
0               Latte              25
1  Americano with Milk             15
2          Cappuccino              15
3           Americano              14
4       Hot Chocolate               6
5             Cortado               5
6            Espresso               5
7               Cocoa               4
```

Insights:
Latte is the most preferred coffee among cash customers, with 25 purchases.

Americano with Milk and Cappuccino are next, each with 15 purchases.

Americano, Hot Chocolate, Cortado, Espresso, and Cocoa are less popular among cash users.

Overall, cash customers mostly choose Latte, Americano with Milk, and Cappuccino.

Findings:

1) Sales Performance by Time

- Weekday Trends

Highest sales: Tuesday, Wednesday, Thursday

Lowest sales: Sunday & Monday

Insight: Coffee sales are driven mainly by work-week routines. Customers are most active from Tuesday to Thursday, while demand drops at the start and end of the week.

- Monthly Trends

Top months: May, June, July

Lowest month: April

Insight: Sales rise from March to May and remain high through June–July, indicating a seasonal growth trend.

Quarterly Trends   Quarter Sales

Q1 - 206

Q2 - 690

Q3 - 237

Insight: Quarter 2 (Apr–Jun) accounts for more than 60% of total sales, making it the most critical revenue period.

2) Product Performance

- Best Selling Coffee Types: Americano with Milk, Latte, and Cappuccino

These three products dominate: Hourly sales, Daily sales, Monthly sales, and Revenue contribution

- Low Demand Products: Espresso, Cocoa, Cortado, and Hot Chocolate

These items consistently show low sales and low revenue.

3) Hourly Purchase Behaviour

- Peak Hours

10 AM – 7 PM is the main sales window.

Highest peak: 10 AM (especially Latte).

Time Period   Top Coffee

Morning (6–11) - Latte

Afternoon (12–5) - Americano with Milk

Evening (6–11) - Americano with Milk / Cappuccino

4) Revenue Insights

- Top Revenue Drivers

Latte → Max 1948 dollars per hour

Cappuccino → Max 1264 dollars per hour

Americano with Milk → Max 992 dollars per hour

These three products generate most of the revenue.

- Weekday Revenue Leaders

Day   Top Coffee

Monday   - Cappuccino

Tuesday - Americano with Milk

Wednesday - Latte

Thursday - Latte

Friday - Latte

Saturday - Americano with Milk

Sunday - Latte

- Monthly Revenue Leaders

Month   Top Coffee

March - Latte

April - Cappuccino

May - Latte

June - Americano with Milk

July - Americano with Milk

5) Customer Behaviour

- Loyal Customers

A small group of card customers generates a large portion of revenue.

Top customer spent 2593 dollars alone.

- Purchase Pattern

Frequent buyers stick to one favourite coffee.

Most loyal preferences: Americano, Latte, and Americano with Milk

- Cash vs Card

Customer Type   Average transaction value

Cash Users - 35.80 dollars

Card Users - 32.88 dollars

Insight: Cash customers spend slightly more per transaction, but their identity is unknown. Although card users dominate the transaction volume, cash transactions have a slightly higher average bill value (35.80 dollars vs 32.88 dollars). This indicates that cash buyers tend to make marginally larger purchases per visit, even though card payments are the preferred payment method overall. Cash transactions have a higher average bill value than card transactions. However, individual cash customers cannot be identified, so customer-level behavioural analysis is not possible for cash payments.

6) Business Problems Identified

Issue & Evidence:

Low Sunday & Monday sales --> Lowest weekday sales

Overdependence on 3 products --> Latte, Cappuccino, Americano with Milk

Many one-time buyers --> Many customers only made 1 purchase

Weak low-demand products --> Espresso, Cocoa, Cortado underperform

Insight: Latte, Cappuccino, and Americano with Milk are the top-selling coffee types because customers prefer smooth, creamy, and less bitter beverages that feel more satisfying and comfortable to drink. These drinks appeal to a wider audience, including first-time customers and casual coffee drinkers.

In contrast, Espresso, Cortado, and Cocoa show low demand because they are either too strong (Espresso), less familiar (Cortado), or not considered a core coffee choice (Cocoa), making them niche products with limited appeal.

Customers clearly favor comfort coffees over strong or unfamiliar options.

Recommendations:

1). Boost Low-Sales Days

Run Sunday–Monday offers

Example: “Buy 1 Latte, Get Espresso at 50% Off”

2). Increase Revenue During Peak Hours

Promote combo offers between 10 AM – 5 PM

Example: Latte + Cappuccino combo deal.

3). Improve Low Performing Products

Bundle Espresso / Cocoa / Cortado with top drinks.

Example: Free Espresso shot with Latte above 50 dollars.

4). Retain High-Value Customers

Offer loyalty rewards to top card customers:

Free drink after every 20 purchases.

Personalized offers based on favourite coffee.

5). Convert One-Time Buyers to Loyal Customers

Provide digital loyalty card for cash users.

Encourage signup for tracking & rewards.

6). Product Strategy

Focus marketing budget on: Latte, Americano with Milk, and Cappuccino

They generate maximum revenue & repeat purchases.

#Action & Impact

- Promote Latte, Cappuccino, Americano with Milk as Signature Drinks --> Increase repeat orders
- Bundle low performers with Latte (e.g., Latte + Cocoa combo) --> Clear dead inventory
- Rename Cortado with simple description --> Improve awareness
- Reduce Espresso size price or make it an add-on --> Increase adoption

Conclusion:

From the analysis above, we have uncovered valuable insights into customer shopping patterns on a daily, weekly and monthly basis. We have identified the most popular, top-selling, high revenue-generating coffee products and observed the shopping trends over time. These findings support smarter business decisions such as optimizing inventory planning, improving and designing the layouts of vending machines, and determining the ideal restock times for coffee products, etc. to maximize sales performance, revenue, and customer satisfaction.

Dashboard:


COFFEE SALES DATA ANALYSIS DASHBOARD
01-03-2024
31-07-2024
Year
All
Quarter
All
Month
All
Weekday
All
Hour
All
Coffee Name
All
Payment Type
All
1133
Total Orders
$37.51K
Total Revenue
$33.11
Average Transaction Value
447
Total Customers
Revenue & Sales Trend Over The Time
Total Revenue
Total Sales
Mar 2024
Apr 2024
May 2024
Jun 2024
Jul 2024
Time Period
Sales By Coffee Type
Americano with Milk
Cappuccino
Americano
Latte
Cortado
Espresso
Hot Chocolate
Cocoa
Revenue by Coffee Type
Latte
$9.0K
Americano with Milk
$8.6K
Cappuccino
$7.3K
Americano
$4.6K
Hot Chocolate
$2.8K
Cortado
$2.7K
Cocoa
$1.3K
Espresso
$1.1K
Total Sales By Part Of The Day
100%
Afternoon
460
Morning
343
Evening
330
71.7%
Revenue and Sales By Payment Type
Total Revenue
Total Sales
$34,323
1044
card
$3,186
89
cash