```python
import os
from dotenv import load_dotenv
from sqlalchemy import create_engine, event

load_dotenv(dotenv_path = "C:/Users/MyDevice/Data Analysis/.env")

user = os.getenv("DB_USER")
password = os.getenv("DB_PASS")
host = os.getenv("DB_HOST")
db = os.getenv("DB_NAME")

engine = create_engine(
    f"mysql+mysqlconnector://{user}:{password}@{host}/{db}"
)

@event.listens_for(engine, "connect")
def set_readonly(dbapi_conn, connection_record):
    cursor = dbapi_conn.cursor()
    cursor.execute("SET SESSION TRANSACTION READ ONLY;")
    cursor.close()

print("Connected in READ-ONLY mode!")
```

In [1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
from sqlalchemy.exc import SQLAlchemyError
from config import engine
import warnings
warnings.filterwarnings('ignore')

try:
    with engine.connect() as connection:
        print("Successfully Connected database in READ ONLY mode")

        table_df = pd.read_sql("SHOW TABLES;", con=connection)

        if not table_df.empty:
            print(f"Total Tables Found : {len(table_df)}")
            print("Sample Tables :")
            print(table_df)
        else:
            print("No tables found in the database")

except SQLAlchemyError as e:
    print("Database connection failed")
    print(f"Error happen: {str(e)}")

except Exception as exc:
    print("Something went wrong")
    print(f"Details: {str(exc)}")
```

```
Connected in READ-ONLY mode!
Successfully Connected database in READ ONLY mode
Total Tables Found : 9
Sample Tables :
  Tables_in_ecommerce_db
0             categories
1              customers
2          inventory_log
3    marketing_campaigns
4            order_items
5                 orders
6               payments
7               products
8                reviews
```

In [2]:
```python
tables_df = pd.read_sql("SHOW TABLES", engine)
tables = tables_df.iloc[:,0].tolist()

for table in tables:
    print(f"Table Name: {table}")
    dataframe = pd.read_sql(f"SELECT * FROM {table}", con=engine)
    print(dataframe.columns)
    print('-'*60 + '\n')
```

```
Table Name: categories
Index(['category_id', 'category_name', 'description'], dtype='object')
------------------------------------------------------------

Table Name: customers
Index(['customer_id', 'first_name', 'last_name', 'email', 'phone', 'gender',
       'age', 'city', 'state', 'country', 'signup_date', 'customer_segment'],
      dtype='object')
------------------------------------------------------------

Table Name: inventory_log
Index(['log_id', 'product_id', 'change_type', 'quantity_change',
       'change_date'],
      dtype='object')
------------------------------------------------------------

Table Name: marketing_campaigns
Index(['campaign_id', 'campaign_name', 'start_date', 'end_date', 'channel',
       'total_spent', 'revenue_generated'],
      dtype='object')
------------------------------------------------------------

Table Name: order_items
Index(['order_item_id', 'order_id', 'product_id', 'quantity', 'unit_price',
       'discount', 'total_price'],
      dtype='object')
------------------------------------------------------------

Table Name: orders
Index(['order_id', 'customer_id', 'order_date', 'status', 'payment_method',
       'total_amount', 'shipping_address', 'city', 'state', 'country'],
      dtype='object')
------------------------------------------------------------

Table Name: payments
Index(['payment_id', 'order_id', 'payment_date', 'payment_method',
       'payment_status', 'amount_paid'],
      dtype='object')
------------------------------------------------------------

Table Name: products
Index(['product_id', 'product_name', 'category_id', 'price', 'cost_price',
       'stock_quantity', 'brand', 'added_date'],
      dtype='object')
------------------------------------------------------------

Table Name: reviews
Index(['review_id', 'product_id', 'customer_id', 'rating', 'review_text',
       'review_date'],
      dtype='object')
------------------------------------------------------------
```

To find datatype for columns

In [3]:

```
table_df = pd.read_sql("SHOW TABLES", engine)
table_list = table_df.iloc[:,0].tolist()

for table in table_list:
```

```
    print(f"Table Name: {table}")
    column_dtype = pd.read_sql(f"SELECT * FROM {table}", engine)
    print(column_dtype.dtypes)
    print('-'*30, '\n')
```

```
Table Name: categories
category_id       int64
category_name    object
description      object
dtype: object
------------------------------

Table Name: customers
customer_id          int64
first_name          object
last_name           object
email               object
phone               object
gender              object
age                  int64
city                object
state               object
country             object
signup_date         object
customer_segment    object
dtype: object
------------------------------

Table Name: inventory_log
log_id                      int64
product_id                  int64
change_type                object
quantity_change             int64
change_date        datetime64[ns]
dtype: object
------------------------------

Table Name: marketing_campaigns
campaign_id            int64
campaign_name         object
start_date            object
end_date              object
channel               object
total_spent          float64
revenue_generated    float64
dtype: object
------------------------------

Table Name: order_items
order_item_id      int64
order_id           int64
product_id         int64
quantity           int64
unit_price       float64
discount         float64
total_price      float64
dtype: object
------------------------------

Table Name: orders
order_id                   int64
customer_id                int64
order_date        datetime64[ns]
status                    object
payment_method            object
```

```
total_amount                 float64
shipping_address              object
city                          object
state                         object
country                       object
dtype: object
------------------------------

Table Name: payments
payment_id                   int64
order_id                     int64
payment_date        datetime64[ns]
payment_method              object
payment_status              object
amount_paid                float64
dtype: object
------------------------------

Table Name: products
product_id          int64
product_name       object
category_id         int64
price             float64
cost_price        float64
stock_quantity      int64
brand              object
added_date         object
dtype: object
------------------------------

Table Name: reviews
review_id       int64
product_id      int64
customer_id     int64
rating          int64
review_text    object
review_date    object
dtype: object
------------------------------
```

In [5]:

```
# Columns that must be converted to datetime

Change_Dtypes = {
    "customers": ["signup_date"],
    "marketing_campaigns": ["start_date", "end_date"],
    "products": ["added_date"],
    "reviews": ["review_date"],
    "inventory_log": ["change_date"],
    "orders": ["order_date"],
    "payments": ["payment_date"]
}

cleaned_data = {}

try:
    table_df = pd.read_sql("SHOW TABLES", engine)
    table_list = table_df.iloc[:, 0].tolist()

    for table in table_list:
```

```python
        df = pd.read_sql(f"SELECT * FROM `{table}`", engine)

        if table in Change_Dtypes:
            print(f"\nFixing datatypes in table: {table}")
            changed_columns = []
            for col in Change_Dtypes[table]:
                if col in df.columns:
                    df[col] = pd.to_datetime(df[col], errors='coerce')
                    changed_columns.append(col)
            print("Columns changed to datetime:", changed_columns)

        cleaned_data[table] = df

    print("\n Datatype conversion completed!")

except Exception as exp:
    print("Unexpected error:", str(exp))
```

```
Fixing datatypes in table: customers
Columns changed to datetime: ['signup_date']

Fixing datatypes in table: inventory_log
Columns changed to datetime: ['change_date']

Fixing datatypes in table: marketing_campaigns
Columns changed to datetime: ['start_date', 'end_date']

Fixing datatypes in table: orders
Columns changed to datetime: ['order_date']

Fixing datatypes in table: payments
Columns changed to datetime: ['payment_date']

Fixing datatypes in table: products
Columns changed to datetime: ['added_date']

Fixing datatypes in table: reviews
Columns changed to datetime: ['review_date']

 Datatype conversion completed!
```

In [6]:

```python
# Count the data

for table in tables:
    print(f"Table Name: {table}")
    data_count = pd.read_sql(f"SELECT COUNT(*) as data_count FROM {table}", engi
    print("Count of records:", data_count)
    print('-'*40)
```

```
Table Name: categories
Count of records: 15
----------------------------------------
Table Name: customers
Count of records: 1000
----------------------------------------
Table Name: inventory_log
Count of records: 3000
----------------------------------------
Table Name: marketing_campaigns
Count of records: 50
----------------------------------------
Table Name: order_items
Count of records: 4500
----------------------------------------
Table Name: orders
Count of records: 1500
----------------------------------------
Table Name: payments
Count of records: 1500
----------------------------------------
Table Name: products
Count of records: 500
----------------------------------------
Table Name: reviews
Count of records: 2000
----------------------------------------
```

In [7]:

```
# Statistical summary for numeric columns

for table in tables:
    print(f"Table Name: {table}")
    data_count = pd.read_sql(f"SELECT * FROM {table}", engine)
    print(data_count.describe())
    print('-'*40)
```

```
Table Name: categories
       category_id
count    15.000000
mean      8.000000
std       4.472136
min       1.000000
25%       4.500000
50%       8.000000
75%      11.500000
max      15.000000
----------------------------------------
Table Name: customers
       customer_id          age
count  1000.000000  1000.000000
mean    500.500000    46.566000
std     288.819436    16.719306
min       1.000000    18.000000
25%     250.750000    32.000000
50%     500.500000    46.000000
75%     750.250000    61.000000
max    1000.000000    75.000000
----------------------------------------
Table Name: inventory_log
            log_id  product_id  quantity_change  \
count  3000.000000  3000.000000      3000.000000
mean   1500.500000   247.407667        35.215333
min       1.000000     1.000000       -10.000000
25%     750.750000   121.000000        -7.000000
50%    1500.500000   249.000000        -3.000000
75%    2250.250000   371.250000        71.000000
max    3000.000000   500.000000       200.000000
std     866.169729   144.224100        62.313551

                         change_date
count                           3000
mean   2024-11-05 13:37:54.449000192
min              2023-11-06 07:02:47
25%    2024-05-11 11:03:14.750000128
50%       2024-11-04 20:29:05.500000
75%    2025-05-05 23:28:12.750000128
max              2025-11-05 04:12:55
std                              NaN
----------------------------------------
Table Name: marketing_campaigns
       campaign_id  total_spent  revenue_generated
count     50.00000      50.0000       5.000000e+01
mean      25.50000  246424.2076       6.307518e+05
std       14.57738  137822.8583       4.832628e+05
min        1.00000    4607.0700       4.320470e+03
25%       13.25000  132130.6800       2.776539e+05
50%       25.50000  252219.4400       4.735390e+05
75%       37.75000  335293.5525       9.363356e+05
max       50.00000  485424.5400       2.105301e+06
----------------------------------------
Table Name: order_items
       order_item_id     order_id   product_id     quantity   unit_price  \
count    4500.000000  4500.000000  4500.000000  4500.000000  4500.000000
mean     2250.500000   750.118667   248.222222     3.494000  1511.416871
std      1299.182435   433.958485   144.779740     1.712423   865.390728
min         1.000000     1.000000     1.000000     1.000000     5.220000
```

```
25%      1125.750000   372.000000   121.000000     2.000000   758.310000
50%      2250.500000   750.000000   245.000000     4.000000  1521.775000
75%      3375.250000  1122.250000   374.000000     5.000000  2251.015000
max      4500.000000  1500.000000   500.000000     6.000000  2999.990000

          discount   total_price
count  4500.000000   4500.000000
mean    138.342236   5140.942138
std     119.801671   4206.265495
min       0.000000      4.770000
25%      39.607500   1741.055000
50%     103.035000   4054.335000
75%     211.185000   7657.665000
max     528.570000  17950.630000
----------------------------------------
Table Name: orders
          order_id  customer_id                     order_date  total_amount
count  1500.000000  1500.000000                           1500   1500.000000
mean    750.500000   496.682000  2024-11-11 06:20:47.182666496   3949.785260
min       1.000000     2.000000            2023-11-06 01:30:10      5.070000
25%     375.750000   254.000000     2024-05-10 06:32:41.500000   1883.960000
50%     750.500000   488.000000     2024-11-23 03:43:18.500000   3869.535000
75%    1125.250000   745.000000     2025-05-05 07:21:45.500000   5992.862500
max    1500.000000   999.000000            2025-11-04 01:48:45   7979.920000
std     433.157015   286.666265                            NaN   2340.402313
----------------------------------------
Table Name: payments
        payment_id     order_id                   payment_date  amount_paid
count  1500.000000  1500.000000                           1500  1500.000000
mean    750.500000   750.500000  2024-11-01 20:55:35.106667008  3996.529160
min       1.000000     1.000000            2023-11-05 22:39:35    11.510000
25%     375.750000   375.750000  2024-05-01 00:04:51.750000128  2003.912500
50%     750.500000   750.500000     2024-11-08 01:32:56.500000  3955.695000
75%    1125.250000  1125.250000  2025-05-01 20:46:05.249999872  6074.192500
max    1500.000000  1500.000000            2025-11-04 23:00:12  7997.390000
std     433.157015   433.157015                            NaN  2354.072416
----------------------------------------
Table Name: products
       product_id  category_id        price   cost_price  stock_quantity
count  500.000000   500.000000   500.000000   500.000000      500.000000
mean   250.500000     7.560000  2498.906200  1621.602920      487.324000
std    144.481833     4.395571  1419.682745   983.354607      290.378764
min      1.000000     1.000000     7.600000     4.590000        6.000000
25%    125.750000     4.000000  1279.620000   818.975000      244.750000
50%    250.500000     7.000000  2528.240000  1597.090000      501.000000
75%    375.250000    11.000000  3704.337500  2333.872500      730.000000
max    500.000000    15.000000  4987.160000  4228.010000     1000.000000
----------------------------------------
Table Name: reviews
         review_id  product_id  customer_id      rating
count  2000.000000  2000.00000   2000.00000  2000.00000
mean   1000.500000   251.77550    499.13700     2.99200
std     577.494589   145.91989    288.55206     1.43037
min       1.000000     1.00000      1.00000     1.00000
25%     500.750000   124.75000    240.75000     2.00000
50%    1000.500000   248.00000    497.00000     3.00000
75%    1500.250000   378.00000    750.00000     4.00000
max    2000.000000   500.00000   1000.00000     5.00000
----------------------------------------
```

Revenue & Sales Trends

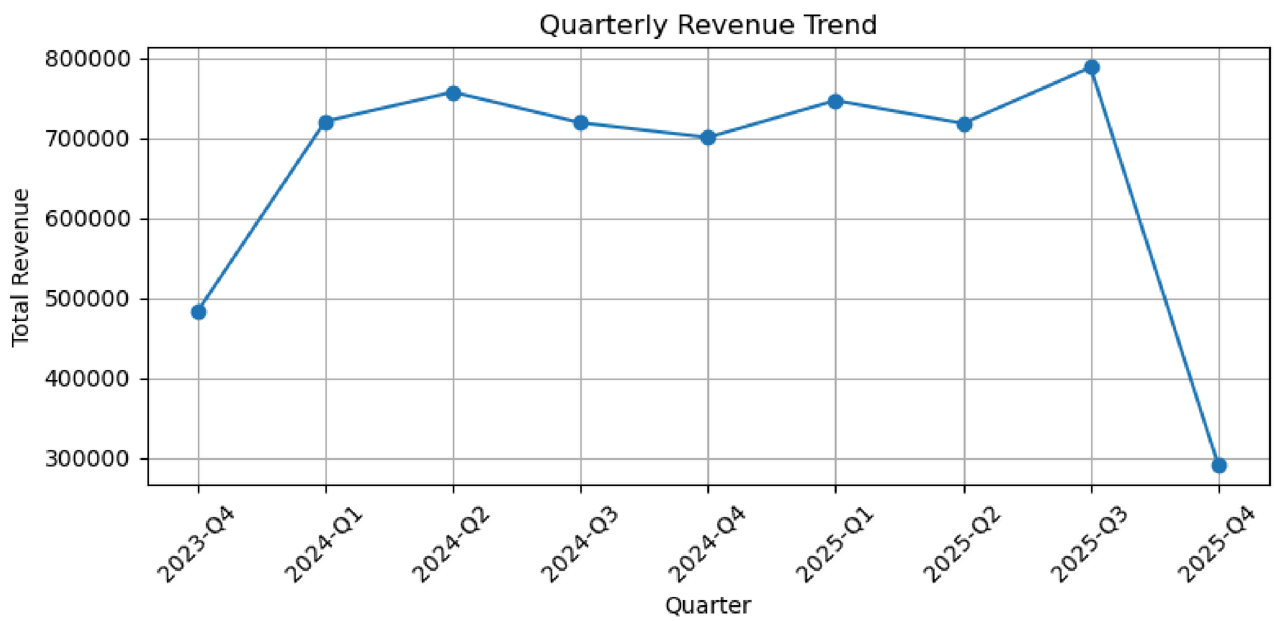
In [8]:
```
# Monthly revenue trend

query = '''
SELECT
    DATE_FORMAT(order_date, '%Y-%m') AS month,
    SUM(total_amount) AS total_revenue,
    COUNT(order_id) AS total_orders,
    ROUND(AVG(total_amount),2) AS avg_order_value
FROM orders
GROUP BY DATE_FORMAT(order_date, '%Y-%m')
ORDER BY DATE_FORMAT(order_date, '%Y-%m');
'''

monthly_trend = pd.read_sql(query, engine)
print(monthly_trend)
```

```
      month  total_revenue  total_orders  avg_order_value
0   2023-11      202280.53            49          4128.17
1   2023-12      280948.93            70          4013.56
2   2024-01      243357.42            55          4424.68
3   2024-02      211796.76            55          3850.85
4   2024-03      265413.98            62          4280.87
5   2024-04      272361.64            68          4005.32
6   2024-05      228315.54            60          3805.26
7   2024-06      256397.45            64          4006.21
8   2024-07      193335.73            46          4202.95
9   2024-08      193689.50            52          3724.80
10  2024-09      331890.68            79          4201.15
11  2024-10      178043.20            49          3633.53
12  2024-11      263584.75            58          4544.56
13  2024-12      258731.40            66          3920.17
14  2025-01      291620.24            76          3837.11
15  2025-02      221728.47            63          3519.50
16  2025-03      233322.99            69          3381.49
17  2025-04      295335.20            73          4045.69
18  2025-05      224931.22            59          3812.39
19  2025-06      197691.67            52          3801.76
20  2025-07      250705.48            67          3741.87
21  2025-08      256310.33            68          3769.27
22  2025-09      280981.84            67          4193.76
23  2025-10      259102.12            66          3925.79
24  2025-11       32800.82             7          4685.83
```

In [10]:
```
# Quarterly revenue trend

query = '''
SELECT
    CONCAT(YEAR(order_date), '-Q', QUARTER(order_date)) AS quarter,
    SUM(total_amount) AS total_revenue,
    COUNT(order_id) AS total_orders,
    ROUND(AVG(total_amount),2) AS avg_order_value
FROM orders
GROUP BY YEAR(order_date), QUARTER(order_date)
ORDER BY YEAR(order_date), QUARTER(order_date);
'''

quarterly_trend = pd.read_sql(query, engine)
```

```
print(quarterly_trend)
print('\n')

# Quarterly revenue plot
plt.figure(figsize=(8,4))
plt.plot(quarterly_trend['quarter'], quarterly_trend['total_revenue'], marker='o
plt.title("Quarterly Revenue Trend")
plt.xlabel("Quarter")
plt.ylabel("Total Revenue")
plt.grid(True)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

```
   quarter  total_revenue  total_orders  avg_order_value
0  2023-Q4      483229.46           119          4060.75
1  2024-Q1      720568.16           172          4189.35
2  2024-Q2      757074.63           192          3943.10
3  2024-Q3      718915.91           177          4061.67
4  2024-Q4      700359.35           173          4048.32
5  2025-Q1      746671.70           208          3589.77
6  2025-Q2      717958.09           184          3901.95
7  2025-Q3      787997.65           202          3900.98
8  2025-Q4      291902.94            73          3998.67
```



Revenue spikes in Q3 2025 (July–September)

This period shows the highest quarterly revenue, driven by increased demand in Electronics and Clothing. Action: Increase marketing spend & inventory for these categories during Q3.

In [11]:
```
# Top 10 Revenue generated products

query = '''
SELECT
    p.product_name,
    COUNT(DISTINCT o.order_id) AS total_orders,
    SUM(oi.total_price) AS total_revenue,
    SUM(oi.quantity) AS total_quantity_sold,
```

```
    ROUND(AVG(oi.total_price), 2) AS avg_item_revenue
FROM products p
JOIN order_items oi ON p.product_id = oi.product_id
JOIN orders o ON oi.order_id = o.order_id
GROUP BY p.product_id, p.product_name
ORDER BY total_revenue DESC
LIMIT 10;
'''

total_revenue = pd.read_sql(query, engine)
print(total_revenue)
```

```
                product_name  total_orders  total_revenue  total_quantity_sold  \
0        Western Harum Elite            14      108657.33                 60.0
1   Quia Consequuntur Mini            11      108091.46                 51.0
2      Repellat Impedit Pro            13      106765.42                 54.0
3         Quidem Recent Pro            17      106635.65                 58.0
4         Optio Molestias X            14      103535.29                 57.0
5        Direction Create X            12      100401.42                 54.0
6   Dolores Education Elite            17       96539.28                 59.0
7             Maxime They X            22       95090.75                 73.0
8       Doloribus Rem Elite            11       93807.66                 46.0
9          Before Dolorem X            14       91962.84                 49.0

   avg_item_revenue
0           7761.24
1           9826.50
2           8212.72
3           6272.69
4           7395.38
5           8366.79
6           5678.78
7           4322.31
8           8527.97
9           6568.77
```

In [12]:

```
# Revenue generated by categories

query = '''
SELECT
    c.category_name,
    COUNT(DISTINCT o.order_id) AS total_orders,
    SUM(oi.total_price) AS total_revenue,
    ROUND(AVG(oi.total_price), 2) AS avg_item_revenue
FROM categories c
JOIN products p ON c.category_id = p.category_id
JOIN order_items oi ON oi.product_id = p.product_id
JOIN orders o ON oi.order_id = o.order_id
GROUP BY c.category_name
ORDER BY total_revenue DESC;
'''

top_categories = pd.read_sql(query, engine)
print(top_categories)
```

```
                category_name  total_orders  total_revenue  avg_item_revenue
0                 Electronics           382     2338558.53           5413.33
1                    Clothing           327     1920356.35           5246.88
2                       Books           329     1821208.02           4869.54
3                     Grocery           295     1817598.14           5474.69
4                Toys & Games           309     1749993.07           4999.98
5                   Furniture           323     1679290.33           4703.89
6                  Automotive           273     1567102.82           5241.15
7                  Stationery           249     1544635.29           5616.86
8    Beauty & Personal Care           281     1528797.83           5062.24
9           Health & Wellness           248     1402401.41           5252.44
10          Sports & Fitness           263     1395368.94           4861.91
11     Jewelry & Accessories           242     1334278.28           5073.30
12            Home Appliances           211     1268502.82           5563.61
13               Pet Supplies           183      945093.39           4797.43
14           Garden & Outdoor           160      821054.40           4801.49
```

In [13]:

```
# revenue by brand

query = '''
SELECT
    p.brand,
    COUNT(DISTINCT o.order_id) AS total_orders,
    SUM(oi.total_price) AS total_revenue,
    ROUND(AVG(oi.total_price),2) AS avg_order_value
FROM products p
JOIN order_items oi ON p.product_id = oi.product_id
JOIN orders o ON oi.order_id = o.order_id
GROUP BY p.brand;
'''

revenue_by_brand = pd.read_sql(query, engine)
print(revenue_by_brand)
```

```
                            brand  total_orders  total_revenue  \
0                     Allen-Kelly            16       88784.26
1          Amble, Bobal and Golla            48      282897.59
2                       Arora PLC            29      156786.86
3    Atkinson, Hayden and Johnson            41      203328.88
4             Avery, Smith and Li             9       42503.26
..                            ...           ...            ...
178         Wyatt, Mann and James            18       89632.13
179             Yohannan and Sons            22       95055.73
180                Yohannan Group             7       52703.08
181         Young, Cook and Smith            61      287901.06
182                  Zuniga-Patel            10       55477.11

     avg_order_value
0            5549.02
1            5893.70
2            5406.44
3            4959.24
4            4722.58
..               ...
178          4717.48
179          4320.72
180          7529.01
181          4569.86
182          5547.71

[183 rows x 4 columns]
```

In [14]:
```
# Top 10 products by quantity sold

query = '''
SELECT
    p.product_name,
    SUM(oi.quantity) AS total_sold,
    SUM(oi.quantity * oi.unit_price) AS total_revenue
FROM products p
JOIN order_items oi ON p.product_id = oi.product_id
GROUP BY p.product_name
ORDER BY total_sold DESC
LIMIT 10;
'''

top_sold_products = pd.read_sql(query,engine)
print(top_sold_products)
```

```
                  product_name  total_sold  total_revenue
0                Maxime They X        73.0       98165.31
1               Summer Her Pro        67.0       88714.04
2  Explicabo Exercitationem Mini        66.0       62265.41
3            Iusto Indicate X        60.0       84251.78
4          Western Harum Elite        60.0      111326.88
5   Repudiandae Repudiandae Plus        59.0       70507.87
6       Dolores Education Elite        59.0       99143.58
7            Quidem Recent Pro        58.0      109400.53
8         Quis Praesentium Max        58.0       78512.50
9                 Illum Up Plus        57.0       64638.65
```

In [15]:
```
# Number of customers per segment

query = '''
```

```
SELECT
    customer_segment,
    COUNT(customer_id) AS total_customers
FROM customers
GROUP BY customer_segment
ORDER BY customer_segment
'''

customers_per_segment = pd.read_sql(query, engine)
print(customers_per_segment)
```

```
  customer_segment  total_customers
0              New              218
1          Premium              148
2          Regular              571
3              VIP               63
```

Regular segment dominates (57% of customers)

Most customers belong to the “Regular” segment, showing consistent repeat purchases. Action: Introduce a structured loyalty program to encourage these Regular customers to move into the Premium tier, increasing long-term value and retention.

In [16]:
```
# Frequently ordered customers

query = '''
SELECT
    CONCAT(first_name, ' ' ,last_name) AS full_name,
    COUNT(o.order_id) AS total_orders,
    SUM(o.total_amount) AS total_amount
FROM customers c
JOIN orders o ON c.customer_id = o.customer_id
GROUP BY c.customer_id, full_name
HAVING COUNT(o.order_id) > 1
ORDER BY total_orders DESC
'''

frequent_customers = pd.read_sql(query, engine)
print(frequent_customers)
```

```
              full_name  total_orders  total_amount
0            Mr Doherty             7      30149.10
1           Aaina Saraf             6      21050.87
2              Tara Raj             6      25857.81
3          Gillian Shaw             6      27469.66
4       Katherine Black             6      13281.17
..                  ...           ...           ...
442        Ishita Chana             2      10182.15
443       Jason Hodgson             2       1797.82
444         Abram Baral             2       9342.67
445            Mr Jones             2       6929.68
446      Dominique Kane             2      10772.25

[447 rows x 3 columns]
```

In [17]:
```
# ROI for each marketing campaign

query = '''
SELECT
```

```
    channel,
    SUM(total_spent) AS total_spent,
    SUM(revenue_generated) AS total_revenue,
    ROUND(((SUM(revenue_generated) - SUM(total_spent)) / SUM(total_spent)) * 100,
        AS ROI_percentage,
    CONCAT(ROUND(((SUM(revenue_generated) - SUM(total_spent)) / SUM(total_spent))
        AS ROI_label
FROM marketing_campaigns
GROUP BY channel
ORDER BY ROI_percentage DESC;
'''

roi_marketing_campaign = pd.read_sql(query, engine)
print(roi_marketing_campaign)
```

```
        channel  total_spent  total_revenue  ROI_percentage ROI_label
0         Email   2936002.51    10117619.51          244.61   244.61%
1    Google Ads   2589749.59     7046707.69          172.10   172.10%
2    Influencer   1521659.90     3787691.81          148.92   148.92%
3     Affiliate   1417817.73     2939163.45          107.30   107.30%
4         Other   1535708.73     3124625.37          103.46   103.46%
5  Social Media   2320271.92     4521781.17           94.88    94.88%
```

Email marketing produces the highest ROI (244%)

Despite relatively moderate spending, email marketing delivers the highest return, making it the most effective channel. Action: Expand the email subscriber base and introduce segmented, personalized campaigns to maximize conversions.

Google Ads & Influencer campaigns also strong (ROI > 145%)

These channels offer a strong balance of high reach and solid profitability. Action: Maintain or slightly increase the budget to capitalize on their consistent performance.

Social Media has lowest ROI (~95%)

Social media campaigns remain profitable, but their efficiency is noticeably lower compared to other channels. Action: Improve audience targeting or reduce ad spend by 10–15% to optimize ROI.

In [18]:
```
# How would you calculate revenue generated vs spend per campaign channel?

query = '''
SELECT
    channel,
    SUM(total_spent) AS total_spent,
    SUM(revenue_generated) AS revenue_generated,
    (SUM(revenue_generated) - SUM(total_spent)) AS profit_or_loss,
    CASE
        WHEN (SUM(revenue_generated) - SUM(total_spent)) > 0 THEN 'Profit'
        WHEN (SUM(revenue_generated) - SUM(total_spent)) = 0 THEN 'Break Even'
        ELSE 'Loss'
    END AS status,
    CONCAT( ROUND(((SUM(revenue_generated) - SUM(total_spent)) / SUM(total_spent)
FROM marketing_campaigns
GROUP BY channel
```

```
ORDER BY ROI DESC;
'''

campaign_channel = pd.read_sql(query, engine)
print(campaign_channel)
```

```
        channel  total_spent  revenue_generated  profit_or_loss  status  \
0  Social Media   2320271.92         4521781.17      2201509.25  Profit
1         Email   2936002.51        10117619.51      7181617.00  Profit
2    Google Ads   2589749.59         7046707.69      4456958.10  Profit
3    Influencer   1521659.90         3787691.81      2266031.91  Profit
4     Affiliate   1417817.73         2939163.45      1521345.72  Profit
5         Other   1535708.73         3124625.37      1588916.64  Profit

       ROI
0   94.88%
1  244.61%
2  172.10%
3  148.92%
4  107.30%
5  103.46%
```

In [19]:

```
# Count of completed vs pending orders

query = '''
SELECT
    CASE
        WHEN status = "Delivered" THEN 'Completed'
        WHEN status = "Pending" THEN 'Pending'
        ELSE 'Other'
    END AS order_status,
    COUNT(order_id) AS total_orders
FROM orders
GROUP BY order_status
ORDER BY total_orders DESC
'''

order_status = pd.read_sql(query, engine)
print(order_status)
```

```
  order_status  total_orders
0        Other           912
1    Completed           299
2      Pending           289
```

Completed orders (299) closely match Pending (289)

High pending orders signal operational delays. Action: Improve warehouse processing or vendor supply chain.

In [20]:

```
# Distribution of Payment Methods

query = '''
SELECT
    payment_method,
    COUNT(*) AS distribution,
    CONCAT(ROUND((COUNT(*) / total_over.total_count) * 100, 2), '%') AS percentag
FROM payments
JOIN (SELECT COUNT(*) AS total_count FROM payments) AS total_over
```

```
GROUP BY payment_method
ORDER BY distribution DESC;
'''

payment_methods = pd.read_sql(query, engine)
print(payment_methods)
```

```
  payment_method  distribution percentage
0    Net Banking           291     19.40%
1            UPI           268     17.87%
2            COD           252     16.80%
3    Credit Card           247     16.47%
4         PayPal           230     15.33%
5     Debit Card           212     14.13%
```

Digital Payment Preference Insight

Net Banking and UPI make up a significant share of total transactions, indicating a clear customer preference for fast and secure digital payments. Action: Offer small instant cashback or discounts on UPI payments to further drive conversions and encourage higher adoption.

PayPal Usage Insight

PayPal accounts for the lowest share of payments (around 15%), suggesting limited usage among domestic customers. Action: Consider disabling PayPal for low-value orders to reduce processing costs, or position it primarily for international customers where PayPal adoption is higher.

In [23]:

```
# Track stock movement from the inventory_log

query = '''
SELECT
    product_id,
    change_type,
    quantity_change,
    DATE(change_date) AS change_date,
    SUM(quantity_change)
        OVER( PARTITION BY product_id ORDER BY change_date ASC
        ROWS BETWEEN UNBOUNDED PRECEDING AND CURRENT ROW
    ) AS cumulative_stock
FROM inventory_log
ORDER BY product_id, change_date;
'''

stock_movement = pd.read_sql(query, engine)
print(stock_movement)
```

```
      product_id change_type  quantity_change change_date  cumulative_stock
0              1        Sale               -4  2023-11-15              -4.0
1              1     Restock              177  2024-02-04             173.0
2              1        Sale               -7  2024-05-11             166.0
3              1     Restock               81  2024-05-31             247.0
4              1        Sale               -9  2024-09-07             238.0
...          ...         ...              ...         ...               ...
2995         500        Sale               -1  2024-04-14             187.0
2996         500        Sale               -8  2024-06-20             179.0
2997         500        Sale               -6  2024-10-02             173.0
2998         500        Sale               -9  2024-10-30             164.0
2999         500      Return                8  2025-08-21             172.0

[3000 rows x 5 columns]
```

In [24]:

```
# cummulative revenue month-by-month

query = '''
SELECT
    month,
    monthly_revenue,
    SUM(monthly_revenue) OVER(ORDER BY month) AS cumulative_revenue
FROM (
    SELECT
        DATE_FORMAT(order_date, '%Y-%m') AS month,
        SUM(total_amount) AS monthly_revenue
    FROM orders
    GROUP BY month
) AS subquery
ORDER BY month
'''

cummulative_revenue = pd.read_sql(query, engine)
print(cummulative_revenue)
```

```
      month  monthly_revenue  cumulative_revenue
0   2023-11        202280.53           202280.53
1   2023-12        280948.93           483229.46
2   2024-01        243357.42           726586.88
3   2024-02        211796.76           938383.64
4   2024-03        265413.98          1203797.62
5   2024-04        272361.64          1476159.26
6   2024-05        228315.54          1704474.80
7   2024-06        256397.45          1960872.25
8   2024-07        193335.73          2154207.98
9   2024-08        193689.50          2347897.48
10  2024-09        331890.68          2679788.16
11  2024-10        178043.20          2857831.36
12  2024-11        263584.75          3121416.11
13  2024-12        258731.40          3380147.51
14  2025-01        291620.24          3671767.75
15  2025-02        221728.47          3893496.22
16  2025-03        233322.99          4126819.21
17  2025-04        295335.20          4422154.41
18  2025-05        224931.22          4647085.63
19  2025-06        197691.67          4844777.30
20  2025-07        250705.48          5095482.78
21  2025-08        256310.33          5351793.11
22  2025-09        280981.84          5632774.95
23  2025-10        259102.12          5891877.07
24  2025-11         32800.82          5924677.89
```

In [25]:

```python
# Moving average of AOV for the last 3 months.

query = '''
SELECT
    month,
    avg_value,
    ROUND(AVG(avg_value) OVER(ORDER BY month ROWS BETWEEN 2 PRECEDING AND CURRENT
FROM (
    SELECT
        DATE_FORMAT(order_date, '%y-%m') AS month,
        ROUND(AVG(total_amount), 2) AS avg_value
    FROM orders
    GROUP BY month
) AS subquery
ORDER BY month
'''

cummulative_aov = pd.read_sql(query, engine)
print(cummulative_aov)
```

	month	avg_value	aov_cummulative
0	23-11	4128.17	4128.17
1	23-12	4013.56	4070.87
2	24-01	4424.68	4188.80
3	24-02	3850.85	4096.36
4	24-03	4280.87	4185.47
5	24-04	4005.32	4045.68
6	24-05	3805.26	4030.48
7	24-06	4006.21	3938.93
8	24-07	4202.95	4004.81
9	24-08	3724.80	3977.99
10	24-09	4201.15	4042.97
11	24-10	3633.53	3853.16
12	24-11	4544.56	4126.41
13	24-12	3920.17	4032.75
14	25-01	3837.11	4100.61
15	25-02	3519.50	3758.93
16	25-03	3381.49	3579.37
17	25-04	4045.69	3648.89
18	25-05	3812.39	3746.52
19	25-06	3801.76	3886.61
20	25-07	3741.87	3785.34
21	25-08	3769.27	3770.97
22	25-09	4193.76	3901.63
23	25-10	3925.79	3962.94
24	25-11	4685.83	4268.46

In [ ]: