Target e-Commerce Analysis

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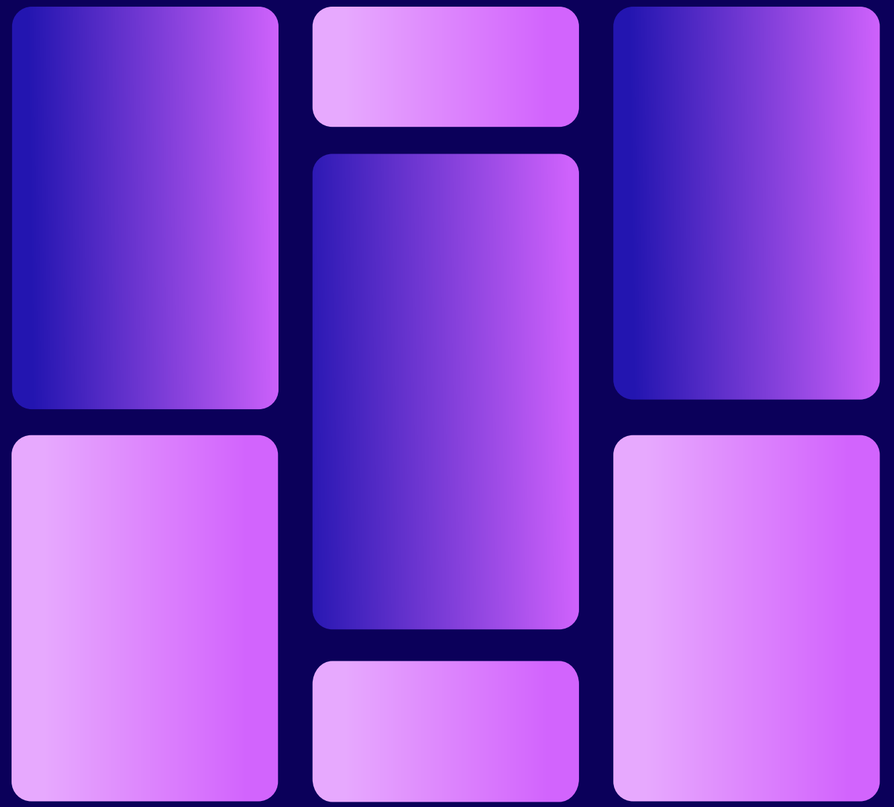
Insights through SQL Queries

Introduction



This project explores key business insights from Target's e-commerce data using SQL and Python.

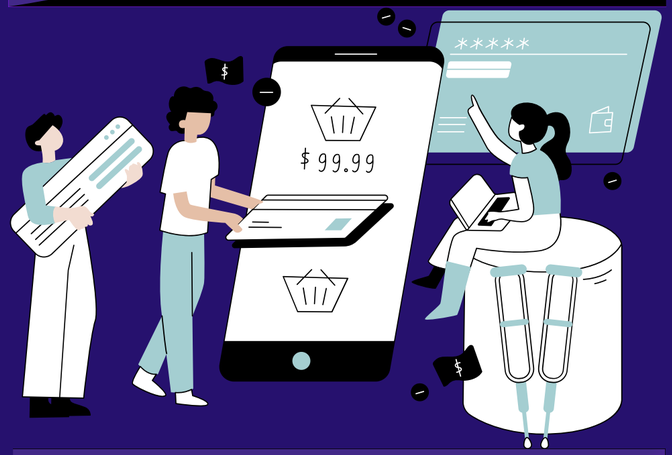
- Extracted insights on customer distribution across states and cities
- Analyzed sales trends and revenue patterns over time
- Identified top product categories and seller performance
- Measured customer retention and repeat purchase behavior
- Calculated revenue contributions and growth metrics using advanced SQL

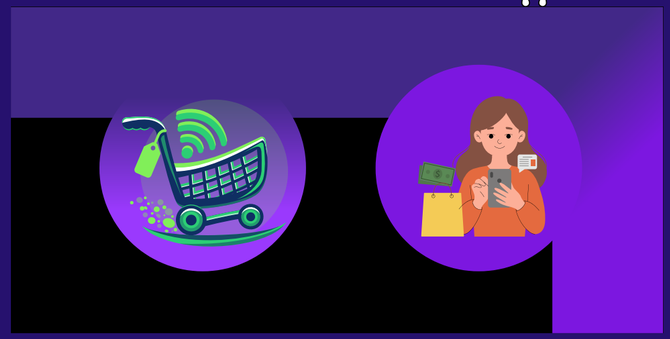
Customer Locations

```
query = """ SELECT DISTINCT customer_city FROM customers"""

cur.execute(query)

data = cur.fetchall()

df = pd.DataFrame(data, columns = ['Cities'])
df.head()
```

	Cities
0	franca
1	sao bernardo do campo
2	sao paulo
3	mogi das cruzes
4	campinas

This query identifies all distinct cities where customers are located, helping understand the geographic reach of the e-commerce platform.



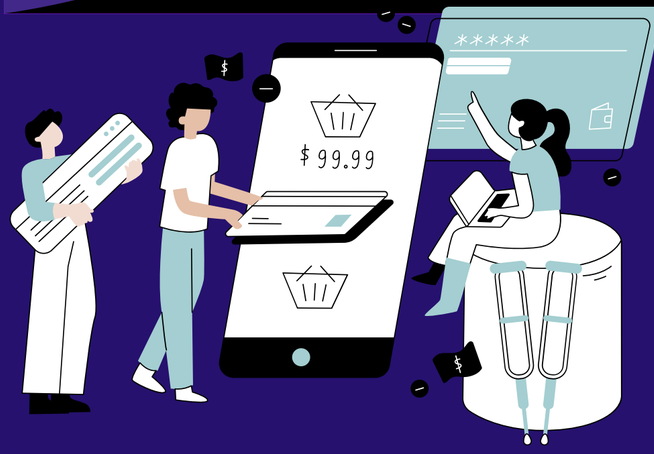


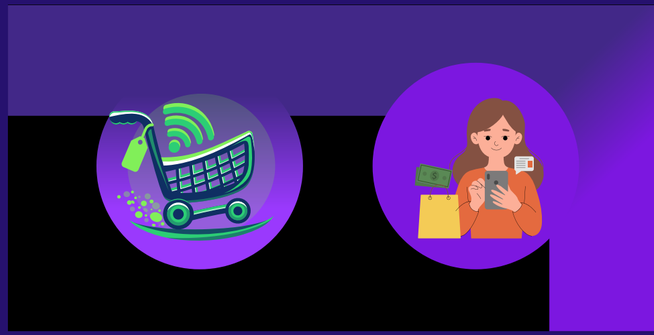
Orders Count – 2017

```
query = """ SELECT COUNT(order_id) FROM orders WHERE YEAR(order_purchase_timestamp) = 2017 """

cur.execute(query)

data = cur.fetchall()

"Total orders placed in 2017 are", data[0][0]
```

```
('Total orders placed in 2017 are', 135303)
```

This query calculates the total number of orders placed in the year 2017, helping identify overall platform activity during that year. It provides insight into annual order volume for business trend analysis.



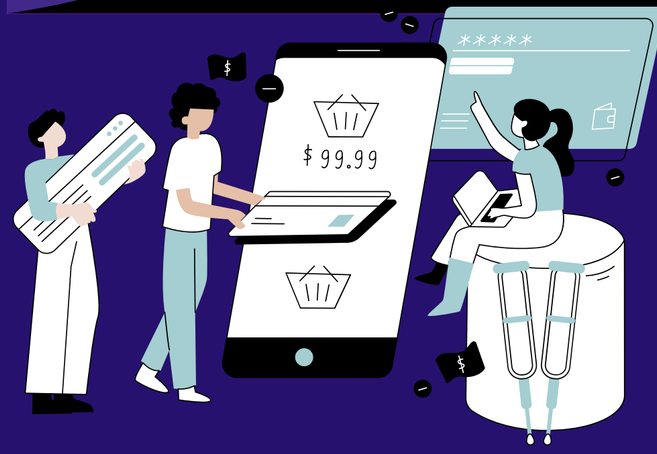


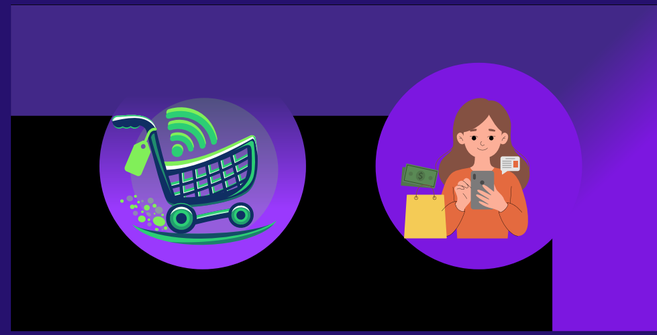
Sales by Category

```
query = """ SELECT UPPER(products.product_category) category,
ROUND(SUM(payments.payment_value),2) sales
FROM products JOIN order_items
ON products.product_id = order_items.product_id
JOIN payments
ON payments.order_id = order_items.order_id
GROUP BY category
"""

cur.execute(query)

data = cur.fetchall()

df = pd.DataFrame(data, columns = ['Category', 'Sales'])
df
```

	Category	Sales
0	PERFUMERY	6080863.92
1	FURNITURE DECORATION	17162116.70
2	TELEPHONY	5842584.61
3	BED TABLE BATH	20550644.05
4	AUTOMOTIVE	10227531.97
...	...	...
69	CDS MUSIC DVDS	14393.16
70	LA CUISINE	34962.36
71	FASHION CHILDREN'S CLOTHING	9428.04
72	PC GAMER	26093.16
73	INSURANCE AND SERVICES	3894.12

This analysis calculates the total sales generated by each product category, helping identify which categories contribute most to overall revenue. It provides valuable insight for product strategy and inventory decisions.



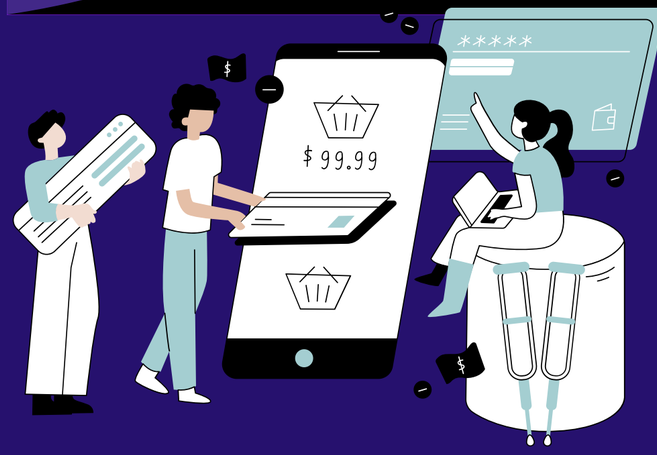


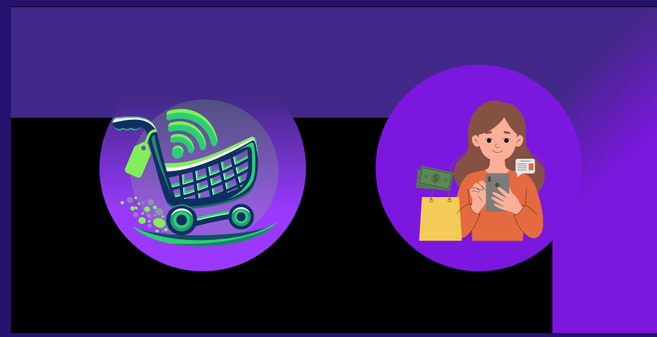
Installment Payment Share

```
query = """ SELECT (SUM(CASE WHEN payment_installments >= 1 THEN 1
ELSE 0 END)) / COUNT(*)*100 FROM payments"""

cur.execute(query)

data = cur.fetchall()

"The percentage of orders that were paid in installments is", data[0][0]
```

```
('The percentage of orders that were paid in installments is',
 Decimal('99.9981'))
```

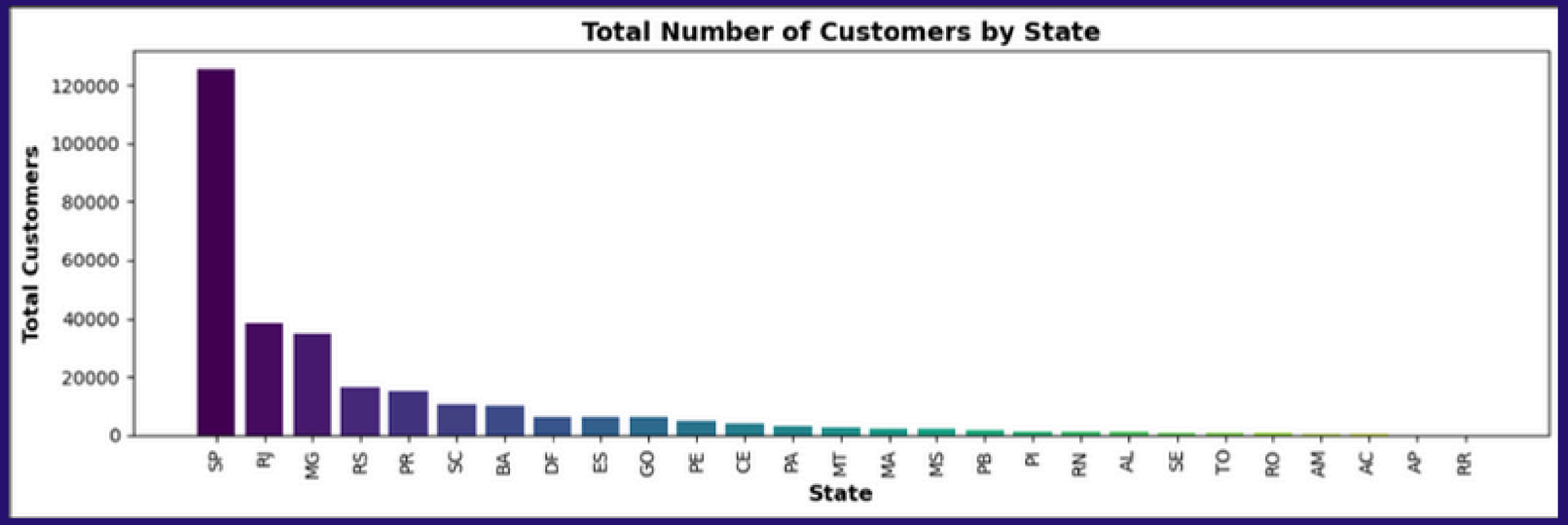
This analysis calculates the percentage of total orders where customers chose to pay in installments, helping us understand payment preferences and financial behavior across the platform.



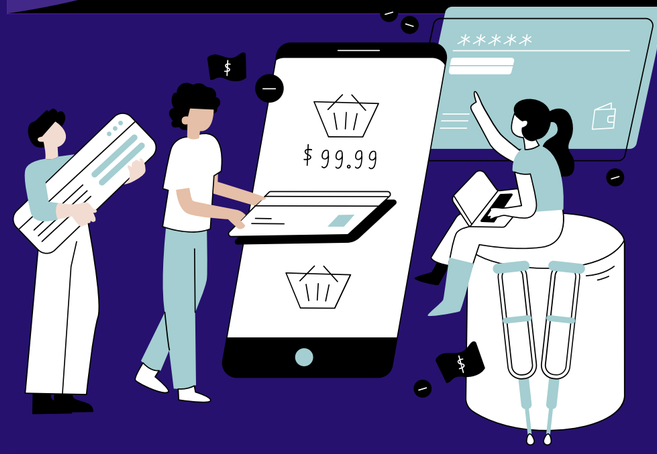


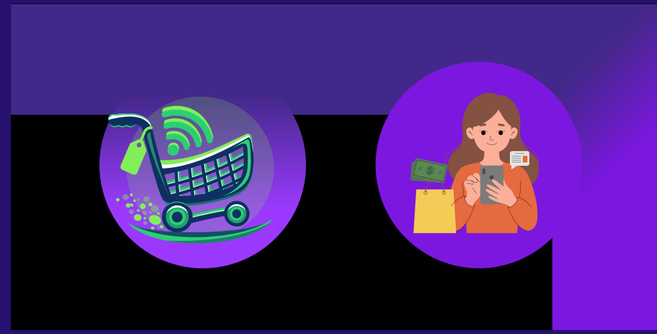
Customer Count by State

```
query = """ SELECT customer_state, COUNT(customer_id)
FROM customers
GROUP BY customer_state
"""

cur.execute(query)

data = cur.fetchall()

df = pd.DataFrame(data, columns = ["State", "Total_Customers"])
df = df.sort_values(by = "Total_Customers", ascending = False)

colors = plt.get_cmap('viridis')(np.linspace(0, 1, len(df["State"])))
plt.figure(figsize=(12, 4))
bars = plt.bar(df["State"], df["Total_Customers"], color=colors)
plt.xlabel("State", fontsize=12, fontweight='bold')
plt.ylabel("Total Customers", fontsize=12, fontweight='bold')
plt.title("Total Number of Customers by State", fontsize=14, fontweight='bold')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```



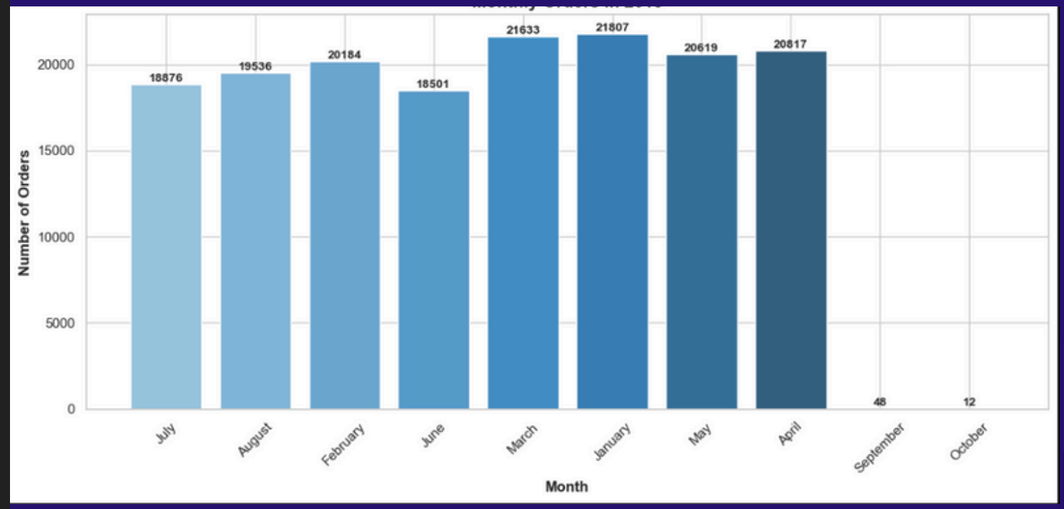
This query counts how many unique customers are present in each state. It helps identify where the business has the strongest customer base and can guide region-specific marketing or expansion strategies.



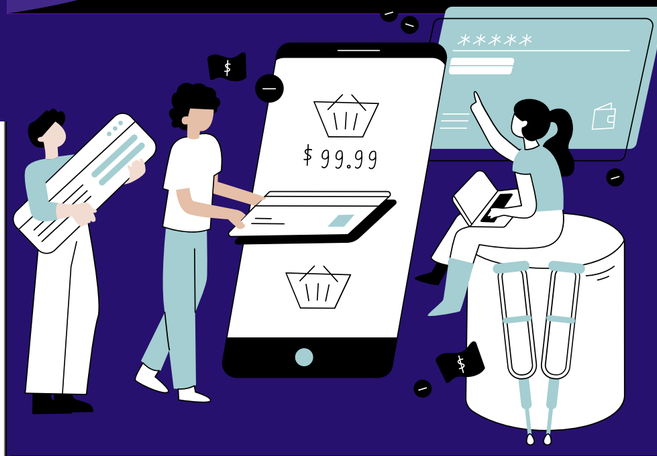


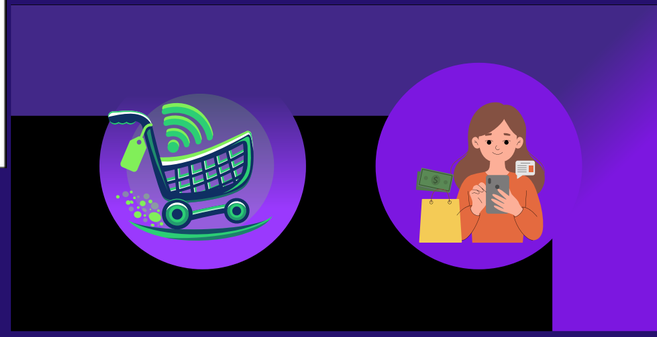
Monthly Orders in 2018

```
query = """ SELECT MONTHNAME(order_purchase_timestamp) months, COUNT(order_id)
FROM orders WHERE YEAR(order_purchase_timestamp) = 2018
GROUP BY months
"""

cur.execute(query)

data = cur.fetchall()

df = pd.DataFrame(data, columns = ['Months', 'Orders'])
o = ["January", "February", "March", "April", "May", "June","July", "August", "September", "October"]

sns.set(style="whitegrid")

plt.figure(figsize=(12, 6))
colors = sns.color_palette("Blues_d", len(df))

bars = plt.bar(df['Months'], df['Orders'], color=colors)

for bar in bars:
    height = bar.get_height()
    plt.text(
        bar.get_x() + bar.get_width() / 2,
        height,
        f'{int(height)}',
        ha='center',
        va='bottom',
        fontsize=10,
        fontweight='bold'
    )

plt.xlabel("Month", fontsize=12, fontweight='bold')
plt.ylabel("Number of Orders", fontsize=12, fontweight='bold')
plt.title("Monthly Orders in 2018", fontsize=14, fontweight='bold')

plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



This query calculates how many orders were placed each month in 2018. It helps identify seasonal trends, peak shopping periods, and fluctuations in customer activity throughout the year.



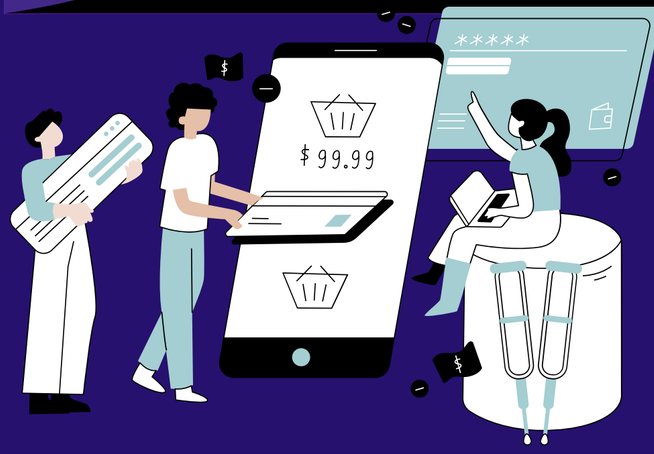


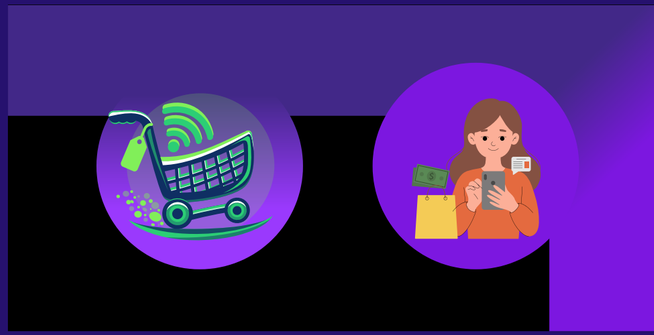
Avg Products per Order by City

```
query = """ WITH count_per_order AS
(SELECT orders.order_id, orders.customer_id, COUNT(order_items.order_id) AS oc
FROM orders JOIN order_items
ON orders.order_id = order_items.order_id
GROUP BY orders.order_id, orders.customer_id)

SELECT customers.customer_city, ROUND(AVG(count_per_order.oc),2) average_orders
FROM customers JOIN count_per_order
ON customers.customer_id = count_per_order.customer_id
GROUP BY customers.customer_city
ORDER BY average_orders DESC;
"""

cur.execute(query)

data = cur.fetchall()

df = pd.DataFrame(data, columns = ['Cities', 'Avg_orders'])
df.head(10)
```

	Cities	Avg_orders
0	padre carvalho	42.00
1	celso ramos	39.00
2	datas	36.00
3	candido godoi	36.00
4	matias olimpio	30.00
5	cidelandia	24.00
6	curralinho	24.00
7	picarra	24.00
8	morro de sao paulo	24.00
9	teixeira soares	24.00

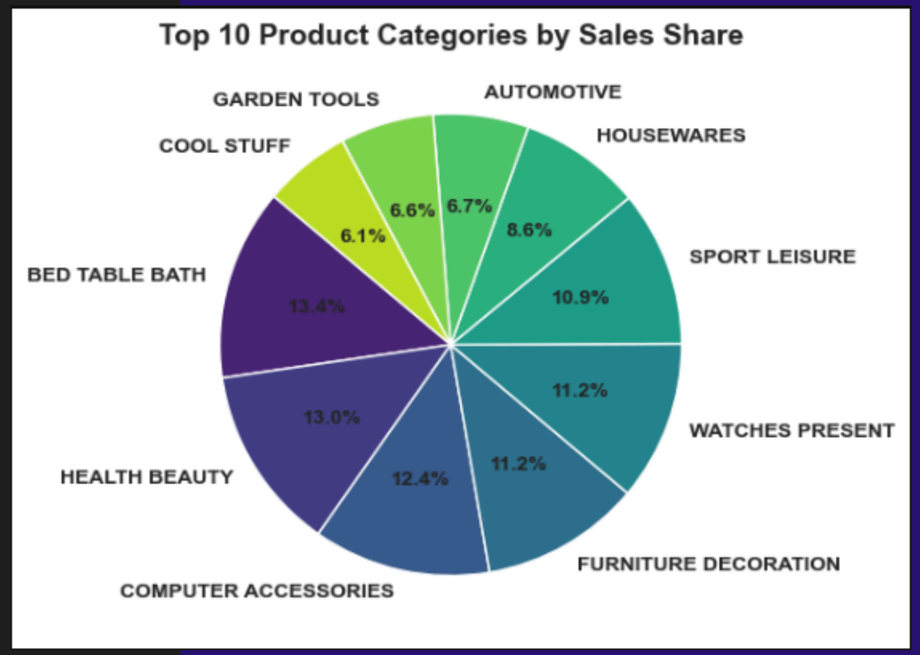
This query calculates the average number of products included in each order, grouped by customer city. It helps identify cities where customers tend to purchase more items per order, which can guide inventory planning and targeted promotions.



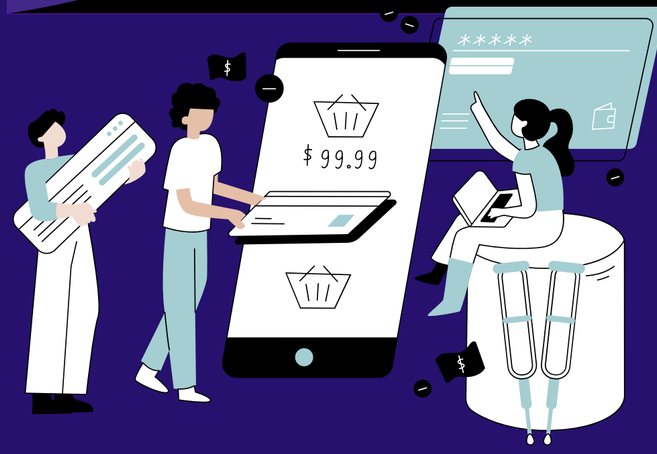


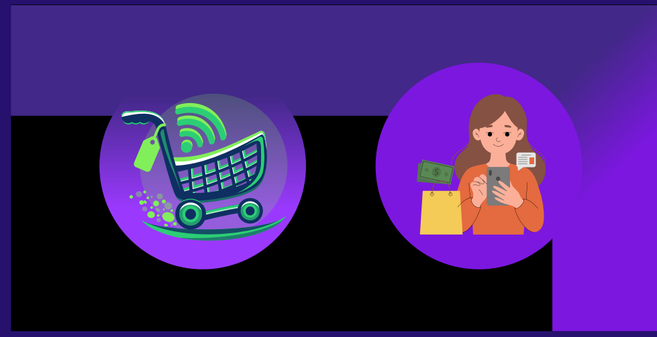
Revenue Share by Product Category

```
query = """ SELECT UPPER(products.product_category) category,
ROUND((SUM(payments.payment_value)/(SELECT SUM(payment_value) FROM payments))*100,2) sales
FROM products JOIN order_items
ON products.product_id = order_items.product_id
JOIN payments
ON payments.order_id = order_items.order_id
GROUP BY category
ORDER BY sales DESC
"""

cur.execute(query)

data = cur.fetchall()

df = pd.DataFrame(data, columns = ['Category', 'Percentage_Distribution'])
df_top = df.head(10)

plt.figure(figsize=(6, 6))
colors = plt.get_cmap("viridis")(np.linspace(0.1, 0.9, len(df_top)))

plt.pie(
    df_top["Percentage_Distribution"],
    labels=df_top["Category"],
    autopct='%1.1f%%',
    startangle=140,
    colors=colors,
    textprops={'fontsize': 10, 'fontweight': 'bold'}
)

plt.title("Top 10 Product Categories by Sales Share", fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()
```



This query calculates how much each product category contributes to the overall revenue, expressed as a percentage. It helps identify the most profitable categories and supports strategic decisions in inventory, marketing, and product focus.



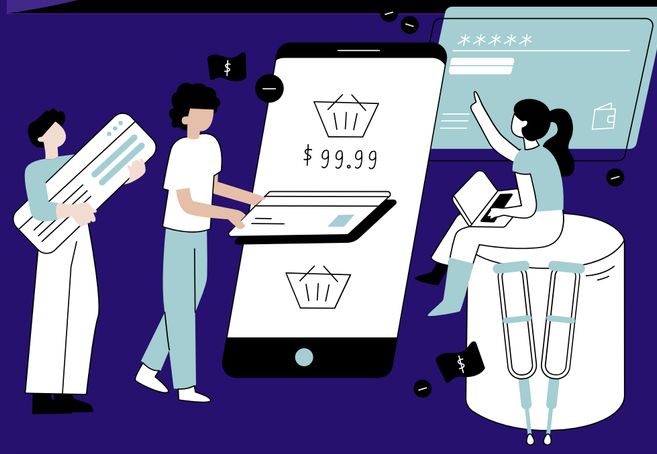


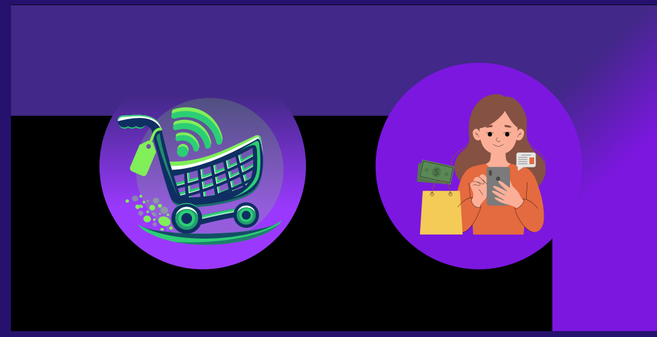
Price vs Purchase Frequency Correlation

```
 query = """SELECT products.product_category,
COUNT(order_items.product_id),
ROUND(AVG(order_items.price), 2)
FROM products JOIN order_items
ON products.product_id = order_items.product_id
GROUP BY products.product_category;
"""
cur.execute(query)

data = cur.fetchall()

df = pd.DataFrame(data, columns = ['Category', 'Order_Count', 'Price'])

arr1 = df['Order_Count']
arr2 = df['Price']

a = np.corrcoef(arr1, arr2)
print("The correlation between price and number of times a product has been purchased is", a[0][1])
```

```
The correlation between price and number of times a product has been purchased is -0.10631514167157563
```

This analysis measures the correlation between product price and purchase frequency, helping determine whether higher- or lower-priced products are bought more often. It can reveal pricing sensitivity and customer purchasing behavior across the catalog.

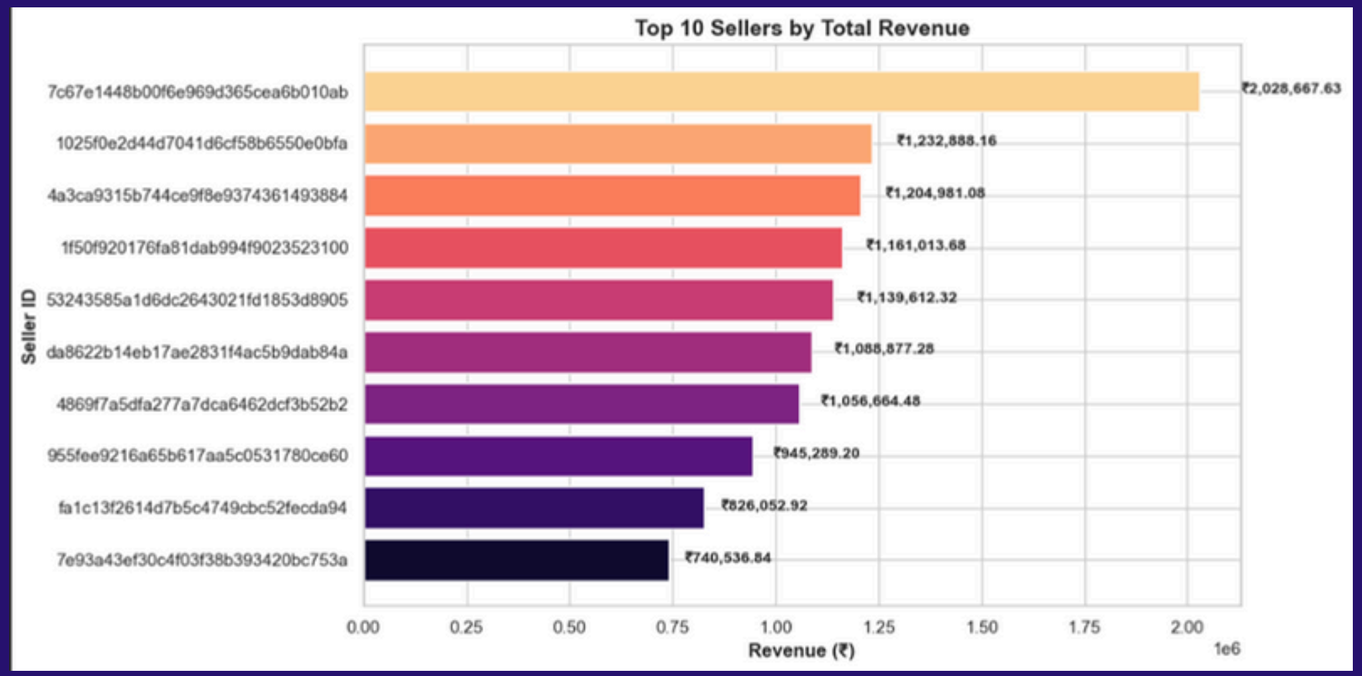




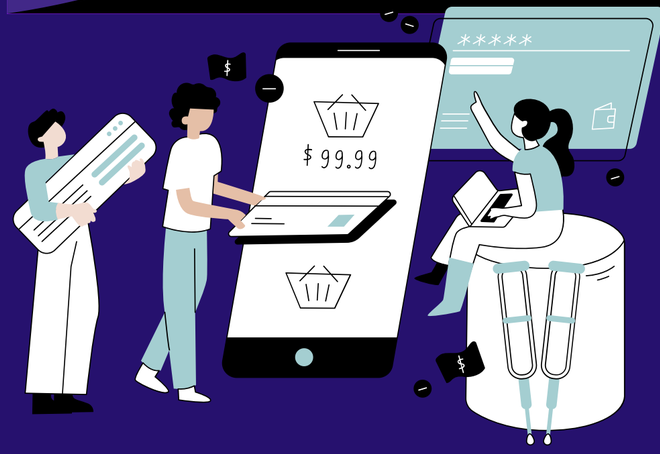
Top Sellers by Revenue

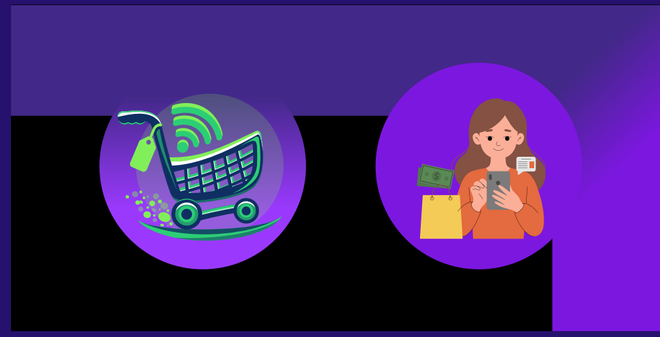
```
query = """ SELECT *, DENSE_RANK() OVER(ORDER BY revenue DESC) AS rn FROM
(SELECT order_items.seller_id, SUM(payments.payment_value) revenue
FROM order_items JOIN payments
ON order_items.order_id = payments.order_id
GROUP BY order_items.seller_id) AS a
"""
cur.execute(query)

data = cur.fetchall()

df = pd.DataFrame(data, columns=['Seller_ID', 'Revenue', 'Rank'])

df_top = df.sort_values(by='Revenue', ascending=False).head(10)

df_top = df_top.sort_values(by='Revenue', ascending=True)

sns.set(style="whitegrid")
```

```
plt.figure(figsize=(12, 6))
colors = sns.color_palette("magma", len(df_top))
bars = plt.barh(df_top['Seller_ID'], df_top['Revenue'], color=colors)

for bar in bars:
    width = bar.get_width()
    plt.text(width + 0.05 * width, bar.get_y() + bar.get_height()/2,
             f'₹{width:,.2f}', va='center', fontsize=10, fontweight='bold')

plt.xlabel("Revenue (₹)", fontsize=12, fontweight='bold')
plt.ylabel("Seller ID", fontsize=12, fontweight='bold')
plt.title("Top 10 Sellers by Total Revenue", fontsize=14, fontweight='bold')

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



This query calculates the total revenue generated by each seller and ranks them in descending order. It helps identify the top-performing sellers on the platform, enabling performance tracking, partnership decisions, and recognition of high-value contributors.



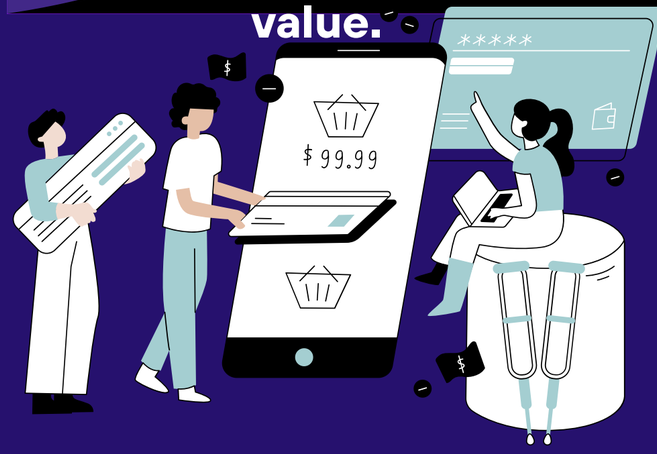


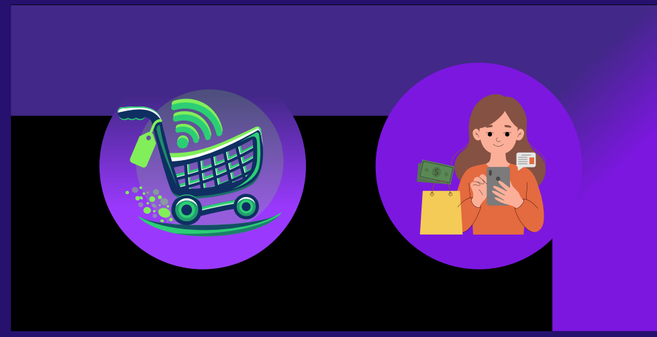
Customer Order Value Moving Average

```
query = """ SELECT customer_id, order_purchase_timestamp, payment,
AVG(payment) OVER(PARTITION BY customer_id ORDER BY order_purchase_timestamp
ROWS BETWEEN 2 PRECEDING AND CURRENT ROW) AS mov_avg
FROM
(SELECT orders.customer_id, orders.order_purchase_timestamp,
payments.payment_value as payment
FROM payments JOIN orders
ON payments.order_id = orders.order_id) AS a
"""
cur.execute(query)

data = cur.fetchall()

df = pd.DataFrame(data, columns = ['Customer_ID', 'Timestamp', 'Payments', 'Moving_Avg'])
df.head(10)
```

	Customer_ID	Timestamp	Payments	Moving_Avg
0	00012a2ce6f8dcda20d059ce98491703	2017-11-14 16:08:26	114.74	114.739998
1	00012a2ce6f8dcda20d059ce98491703	2017-11-14 16:08:26	114.74	114.739998
2	00012a2ce6f8dcda20d059ce98491703	2017-11-14 16:08:26	114.74	114.739998
3	00012a2ce6f8dcda20d059ce98491703	2017-11-14 16:08:26	114.74	114.739998
4	00012a2ce6f8dcda20d059ce98491703	2017-11-14 16:08:26	114.74	114.739998
5	00012a2ce6f8dcda20d059ce98491703	2017-11-14 16:08:26	114.74	114.739998
6	000161a058600d5901f007fab4c27140	2017-07-16 09:40:32	67.41	67.410004
7	000161a058600d5901f007fab4c27140	2017-07-16 09:40:32	67.41	67.410004
8	000161a058600d5901f007fab4c27140	2017-07-16 09:40:32	67.41	67.410004
9	000161a058600d5901f007fab4c27140	2017-07-16 09:40:32	67.41	67.410004

This query calculates the moving average of order values per customer, showing how each customer's spending behavior changes over time. It helps identify trends in purchasing patterns, loyalty, and potential shifts in customer value.

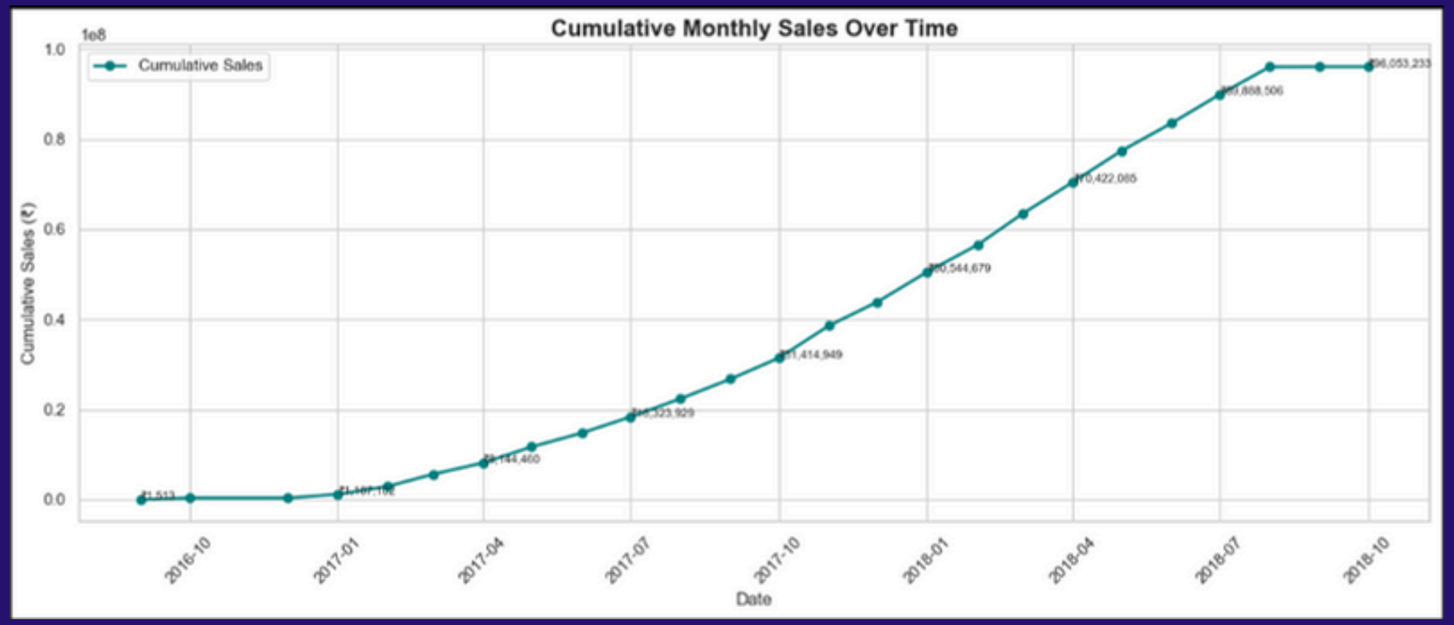




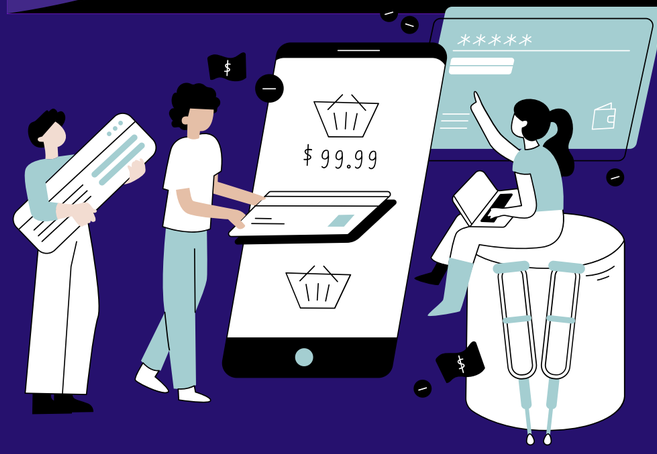
Monthly Cumulative Sales by Year

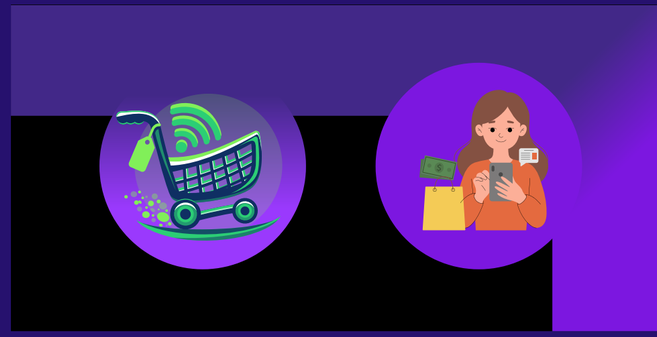
```
query = """ SELECT years, months, payment, SUM(payment)
OVER(ORDER BY years, months) Cumulative_sales
FROM
(SELECT YEAR(orders.order_purchase_timestamp) AS years,
MONTH(orders.order_purchase_timestamp) AS months,
ROUND(SUM(payments.payment_value), 2) AS payment
FROM orders JOIN payments
ON orders.order_id = payments.order_id
GROUP BY years, months
ORDER BY years, months) AS a
"""
cur.execute(query)

data = cur.fetchall()

df = pd.DataFrame(data, columns=['Year', 'Month', 'Monthly_Sales', 'Cumulative_Sales'])

df['Date'] = pd.to_datetime(df[['Year', 'Month']].assign(DAY=1))

df = df.sort_values(by='Date')
```

```
sns.set(style="whitegrid")

plt.figure(figsize=(14, 6))

plt.plot(df['Date'], df['Cumulative_Sales'],
         marker='o', linestyle='-', linewidth=2, color='teal', label='Cumulative Sales')

for i, value in enumerate(df['Cumulative_Sales']):
    if i % 3 == 0:  # annotate every 3rd point to reduce clutter
        plt.text(df['Date'].iloc[i], value + 10000, f"₹{value:,.0f}", fontsize=8)

plt.title("Cumulative Monthly Sales Over Time", fontsize=16, fontweight='bold')
plt.xlabel("Date", fontsize=12)
plt.ylabel("Cumulative Sales (₹)", fontsize=12)
plt.xticks(rotation=45)
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```



This query calculates the running total of sales for each month within a given year, allowing you to track how revenue accumulates over time. It helps visualize sales momentum, compare growth across years, and identify peak periods.



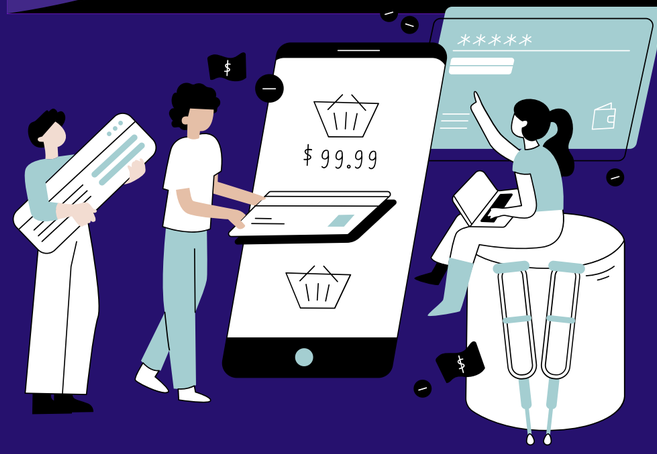


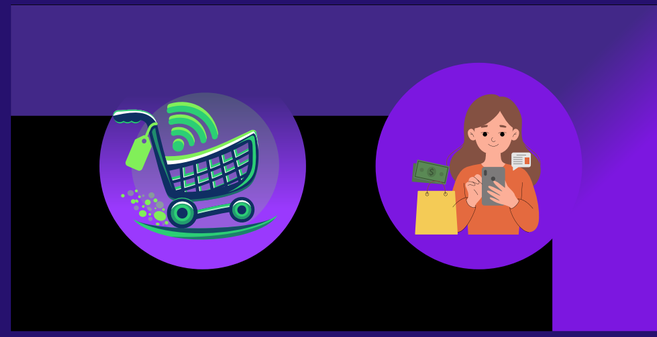
Year-over-Year Sales Growth

```
query = """ WITH yearly_sales AS (
    SELECT
        YEAR(o.order_purchase_timestamp) AS year,
        ROUND(SUM(p.payment_value), 2) AS total_revenue
    FROM orders o
    JOIN payments p ON o.order_id = p.order_id
    GROUP BY YEAR(o.order_purchase_timestamp)
    ORDER BY year
)

SELECT
    year,
    total_revenue,
    ROUND(
        (total_revenue - LAG(total_revenue) OVER(ORDER BY year))
        / LAG(total_revenue) OVER(ORDER BY year) * 100, 2
    ) AS yoy_growth_percentage
FROM yearly_sales;
"""
cur.execute(query)

data = cur.fetchall()

df = pd.DataFrame(data, columns=['Year', 'Total_Revenue', 'YoY_Growth'])
df
```

	Year	Total_Revenue	YoY_Growth
0	2016	356174.04	NaN
1	2017	43498480.37	12112.7
2	2018	52198578.31	20.0

This query calculates the percentage growth in total sales from one year to the next. It helps measure the company's performance over time, assess business expansion, and identify years of strong or weak revenue growth.





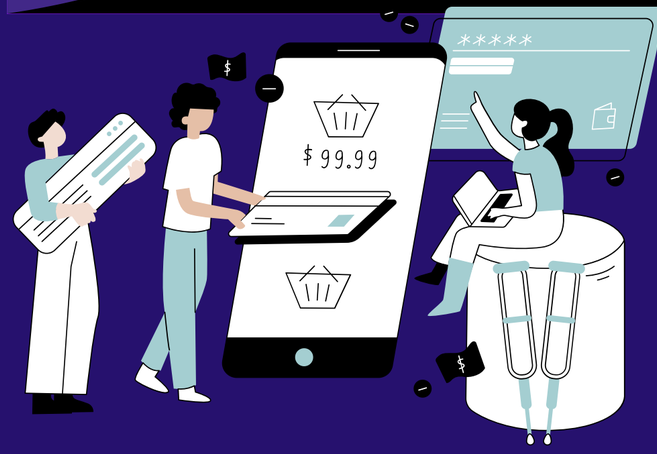
Month Customer Retention Rate

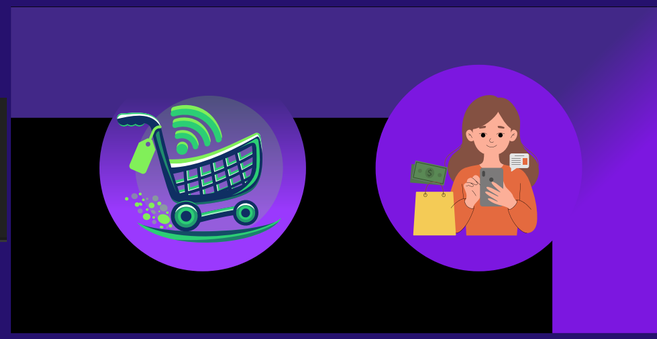
```
query = """ WITH
a AS (
    SELECT customers.customer_id,
           MIN(orders.order_purchase_timestamp) AS first_order
    FROM customers
    JOIN orders ON customers.customer_id = orders.customer_id
    GROUP BY customers.customer_id
),
b AS (
    SELECT a.customer_id,
           COUNT(DISTINCT orders.order_purchase_timestamp) AS repeat_orders
    FROM a
    JOIN orders ON orders.customer_id = a.customer_id
              AND orders.order_purchase_timestamp > a.first_order
              AND orders.order_purchase_timestamp < DATE_ADD(a.first_order, INTERVAL 6 MONTH)
    GROUP BY a.customer_id
)

SELECT
    100 * (COUNT(DISTINCT b.customer_id) / COUNT(DISTINCT a.customer_id)) AS repeat_rate_percentage
FROM a
LEFT JOIN b ON a.customer_id = b.customer_id;

"""
cur.execute(query)

data = cur.fetchall()

data
```

```
[(Decimal('0.0000'),)]
```

```
# Why is the output NULL?
# This query is attempting to calculate the percentage of new customers (those with a first order) who returned to place another order within 6 months.
# However, it returns NULL because the denominator — COUNT(DISTINCT b.customer_id) — becomes zero, which leads to a division by zero.
# This happens when no customers placed a second order within 6 months of their first order, based on the available data.
```

This query calculates the retention rate by identifying customers who placed a second order within 6 months of their first purchase. It reflects customer loyalty and helps evaluate the effectiveness of onboarding, engagement, and re-marketing strategies.

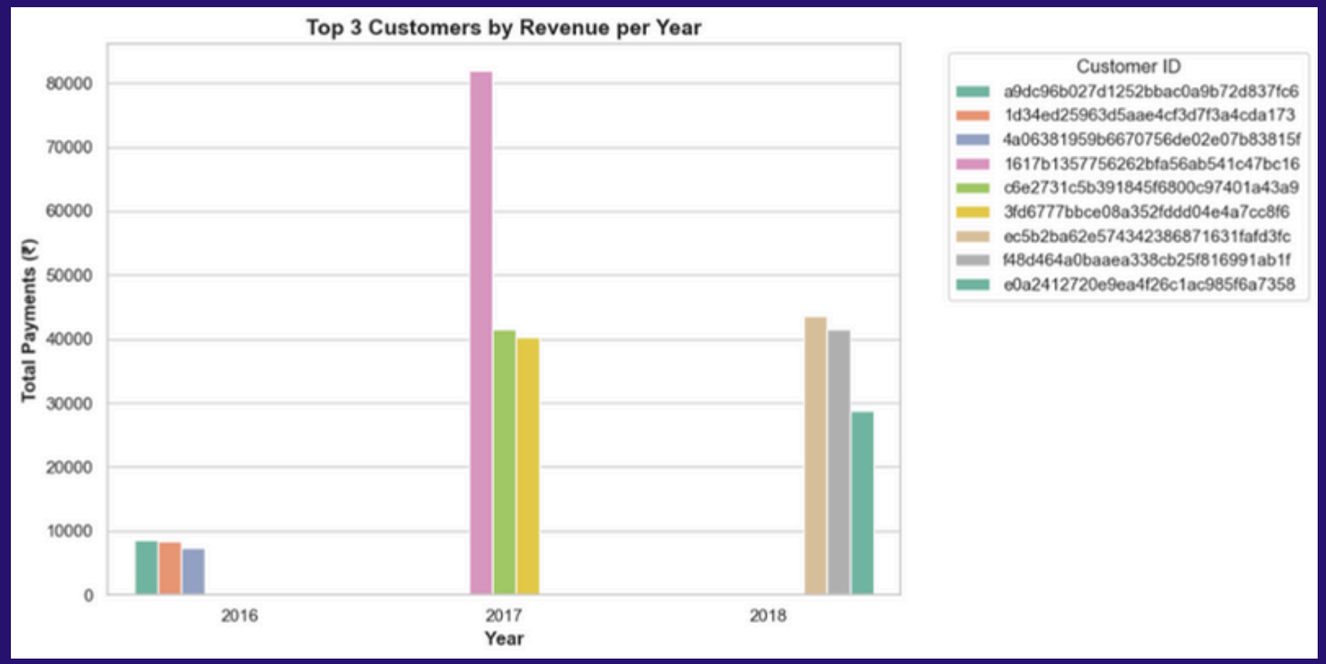




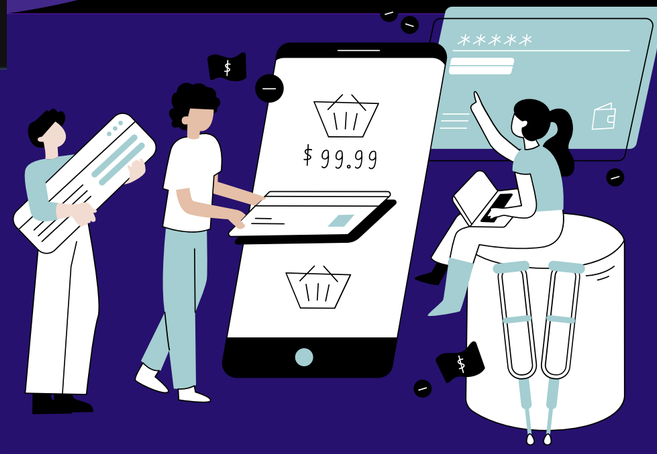
Top 3 Customers by Yearly Spend

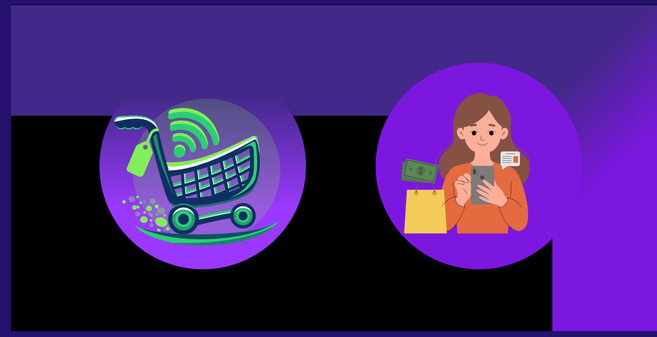
```
query = """ SELECT years, customer_id, payment, d_rank
FROM
(SELECT YEAR(orders.order_purchase_timestamp) years,
orders.customer_id,
SUM(payments.payment_value) payment,
DENSE_RANK()
OVER(PARTITION BY YEAR(orders.order_purchase_timestamp)
ORDER BY SUM(payments.payment_value)DESC) d_rank
FROM orders JOIN payments
ON payments.order_id = orders.order_id
GROUP BY YEAR(orders.order_purchase_timestamp), orders.customer_id) AS a

WHERE d_rank <= 3

"""
cur.execute(query)

data = cur.fetchall()
```

```
df = pd.DataFrame(data, columns=['Year', 'Customer_ID', 'Total_Payment', 'Rank'])

df['Year'] = df['Year'].astype(str)

plt.figure(figsize=(12, 6))
sns.set(style="whitegrid")

sns.barplot(data=df, x='Year', y='Total_Payment', hue='Customer_ID', palette='Set2')

plt.title("Top 3 Customers by Revenue per Year", fontsize=14, fontweight='bold')
plt.xlabel("Year", fontsize=12, fontweight='bold')
plt.ylabel("Total Payments (₹)", fontsize=12, fontweight='bold')
plt.legend(title='Customer ID', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()

plt.show()
```



This query identifies the top 3 highest-spending customers for each year, based on their total purchase value. It highlights the most valuable customers annually and supports VIP engagement, loyalty programs, and personalized marketing efforts.





Conclusion

This e-Commerce sales analysis project provided a comprehensive view of Target's digital retail performance. By leveraging SQL and Python, I was able to:

- Uncover customer distribution and purchasing patterns
- Analyze sales performance across products, cities, and timeframes
- Identify top-performing sellers and high-value customers
- Measure business growth, retention rates, and revenue contributions

These insights empower data-driven decisions in marketing, sales strategy, inventory planning, and customer relationship management. The project demonstrates how structured data and thoughtful analysis can turn raw transactions into actionable business intelligence.

Thank You for Your Attention

Connecting for Future Opportunities

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💬 **Open to feedback, collaborations, internships, and data roles — let's connect!**