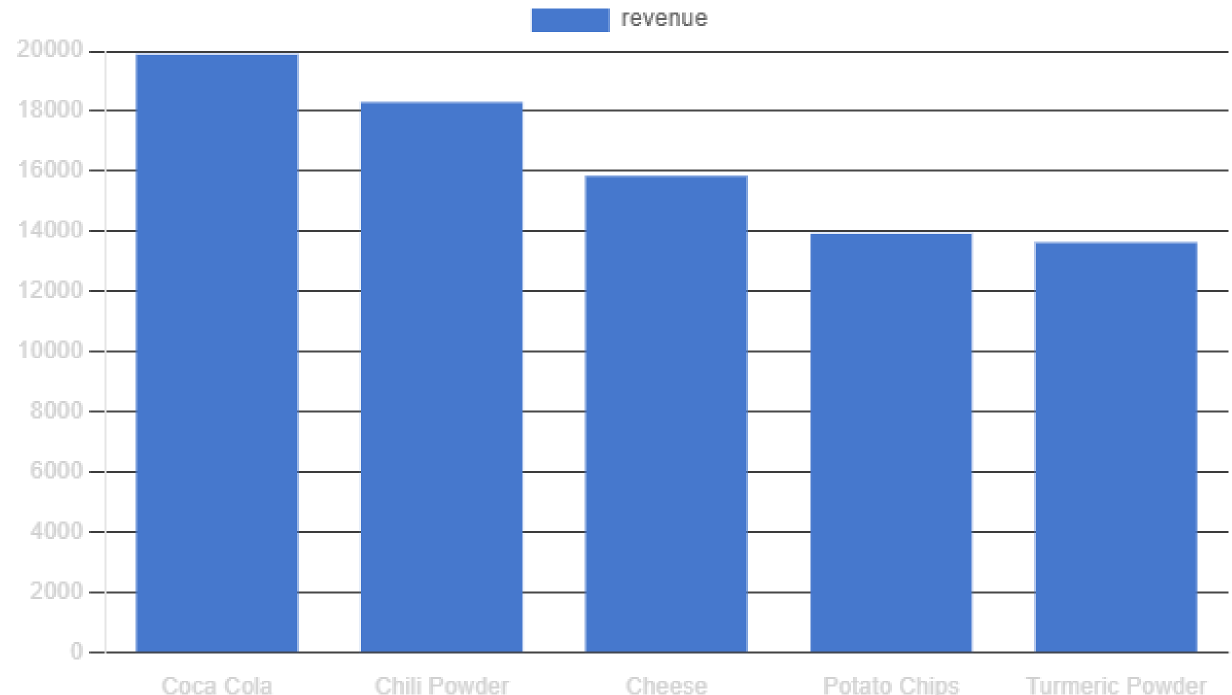
Retail Analytics Case Study -SK MART

📝 Case Study Overview

In this case study, I analyzed sales, customer behavior, product performance, inventory status, and marketing effectiveness for **SK Mart** — a growing retail chain operating in key areas of Dhaka, Bangladesh. Using **SQL**, I explored real-world business problems such as identifying top-performing products, customer purchase patterns, low-stock risks, and the impact of marketing campaigns across platforms like Facebook and YouTube. The goal of this analysis is to provide actionable insights that can help optimize SK Mart's operations and drive data-informed decision-making.

🧠 Business Questions:

1. What are the top 5 best-selling products by quantity and revenue?



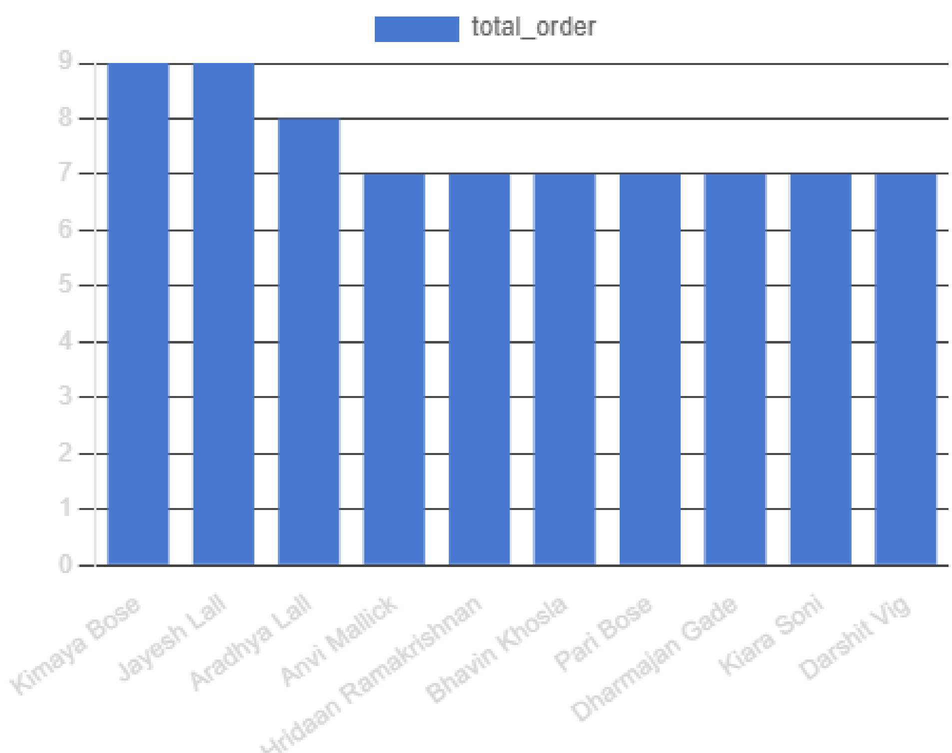
The results show that **Coca Cola** leads in both metrics, followed closely by **Chili Powder, Cheese, Potato Chips, and Turmeric Powder**. These products contribute significantly to overall sales, indicating strong **customer demand** across both branded snacks and essential grocery items.

```
with best_selling_products as (
select
   p.name,
   sum(o.quantity) as total_order,
   sum(o.price) as revenue,
   rank() over(order by sum(o.price) desc, sum(o.quantity) desc) as rank_
from products as p
inner join order_items as o on p.id = o.product_id
group by 1
```

```
)
select *
from best_selling_products
where rank_ <=5;
```

---

2. **Which customers placed the most orders?**



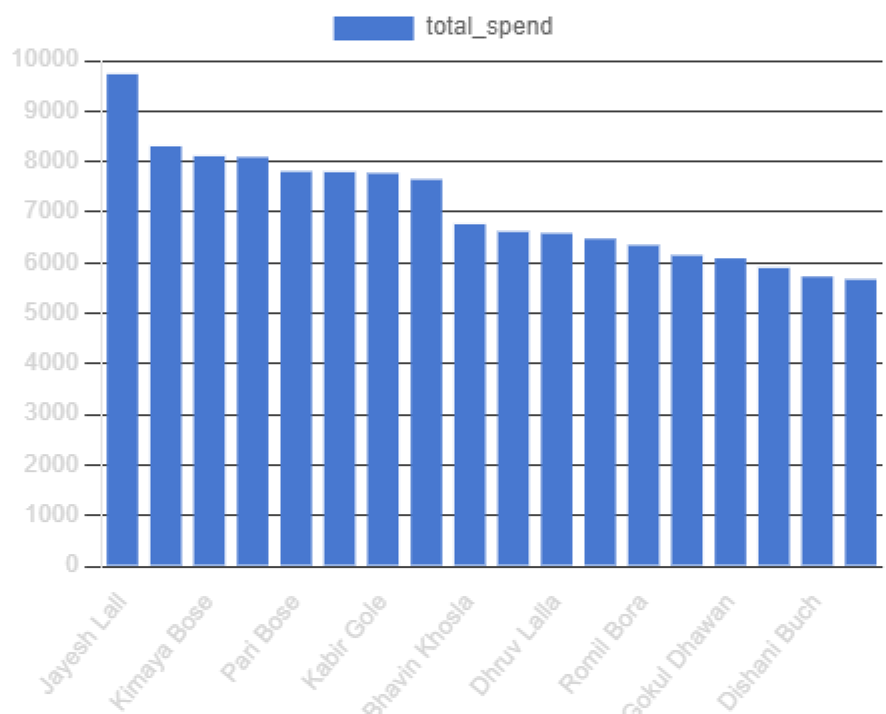
Using SQL, I identified the most frequent buyers at SK Mart based on total order volume.
Kimaya Bose and **Jayesh Lall** lead the list with **9 orders each**, followed closely by **Aradhya Lall** with 8 orders. Several other loyal customers, including **Anvi Mallick**, **Hridaan Ramakrishnan**, and **Pari Bose**, placed 7 orders each. This insight

highlights a group of highly engaged customers who are likely to respond well to loyalty programs or targeted promotions.

```
select
   c.full_name,
   count(o.id) as total_order,
   rank() over(order by count(o.id) desc)
from customers as c
inner join orders as o on c.id = o.customer_id
group by 1
```

---

3. **Who are the top customers based on total spending?**



To identify SK Mart's most valuable customers, I analyzed total spending per customer using SQL. This insight helps prioritize high-value segments for loyalty programs or personalized offers.

🟢 Key Finding:

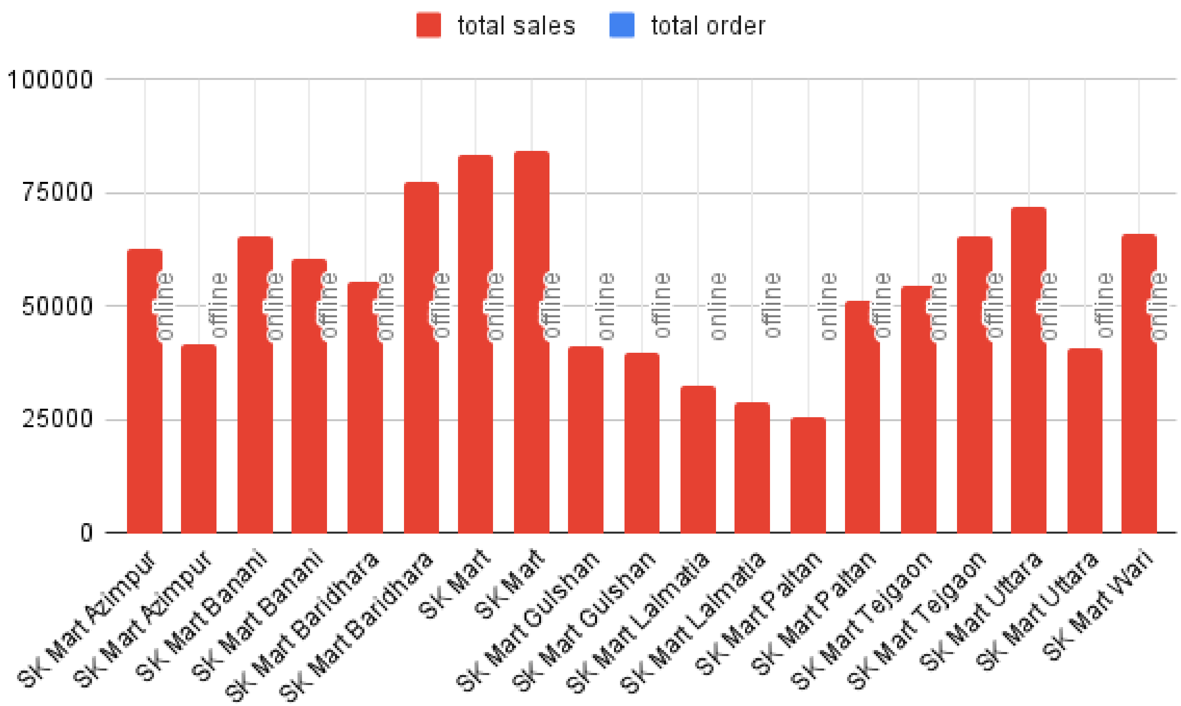
> The top customer is Jayesh Lall, with a total spend of ৳9,729.33, followed closely by Lall (৳8,302.81) and Kimaya Bose (৳8,107.54).

These top spenders represent significant revenue opportunities and should be the focus of customer retention and VIP marketing strategies.

```
select
   c.full_name,
   sum(o.total_amount) as total_spend,
   rank() over(order by sum(o.total_amount) desc)
from customers as c
inner join orders as o on c.id = o.customer_id
group by 1
```

---

4. Compare online vs. offline sales for each store.



In this analysis, I compared online and offline sales across SK Mart's outlets to understand channel performance by location.

🔍 Key Findings:

Online sales outperformed offline in most locations like Azimpur, Banani, and Uttara, indicating a strong digital customer base.

Offline sales were higher in locations like Baridhara, Paltan, and Tejgaon, suggesting stronger foot traffic or walk-in preference.

In Dhanmondi and Gulshan, online and offline performance was nearly balanced, showing potential for omnichannel optimization.

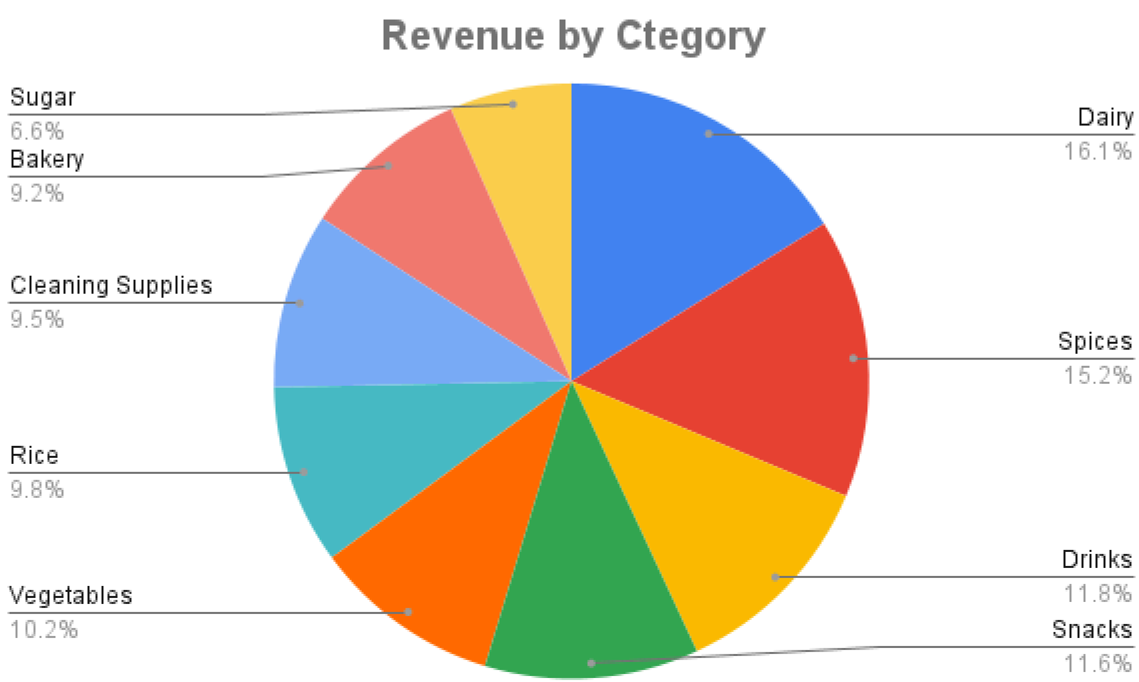
This insight can help SK Mart tailor its channel-specific strategies—such as boosting offline promotions in high-walk-in areas and enhancing delivery or digital ads in online-heavy zones.

```
select
   s.store_name,
   o.order_type,
   count(distinct o.id) as total_orders,
```

```
    sum(oi.quantity * oi.price) as total_sales
from orders o
join order_items oi on o.id = oi.order_id
join stores s on o.store_id = s.id
group by 1, 2;
```

---

5. **Which product categories generate the highest and lowest revenue?**



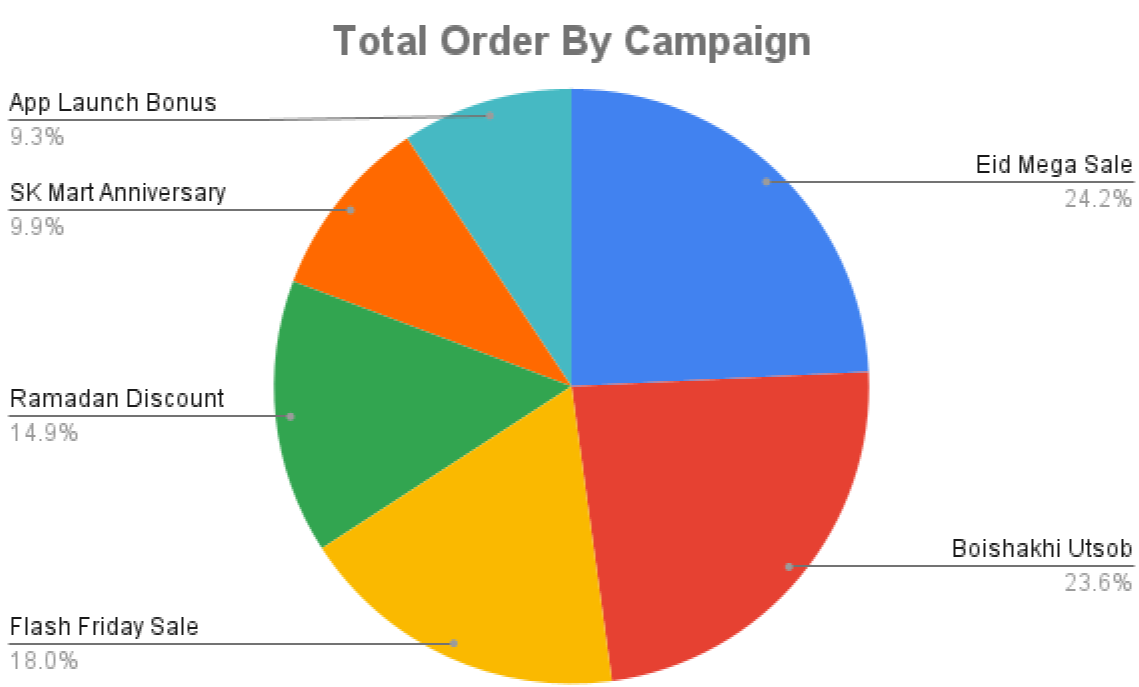
To understand which product categories drive the business, I analyzed the total revenue generated by each category across all SK Mart outlets. The data revealed that **Dairy** is the highest-performing category, bringing in over **৳167,000**, followed closely by **Spices** and **Drinks**. These three categories alone contribute a significant share of overall sales, indicating strong and consistent demand.

On the other end of the spectrum, categories like **Sugar**, **Bakery**, and **Cleaning Supplies** generated comparatively lower revenue, suggesting potential areas for promotional focus or inventory optimization. These insights help SK Mart prioritize stock, marketing, and shelf space to maximize revenue across locations.

```
select
   c.category_name,
   sum(oi.quantity * oi.price) as revenue
from categories as c
inner join products as p on c.id = p.category_id
inner join order_items as oi on p.id = oi.product_id
group by 1
order by 2 desc;
```

---

6. **Which marketing campaign brought in the most orders?**

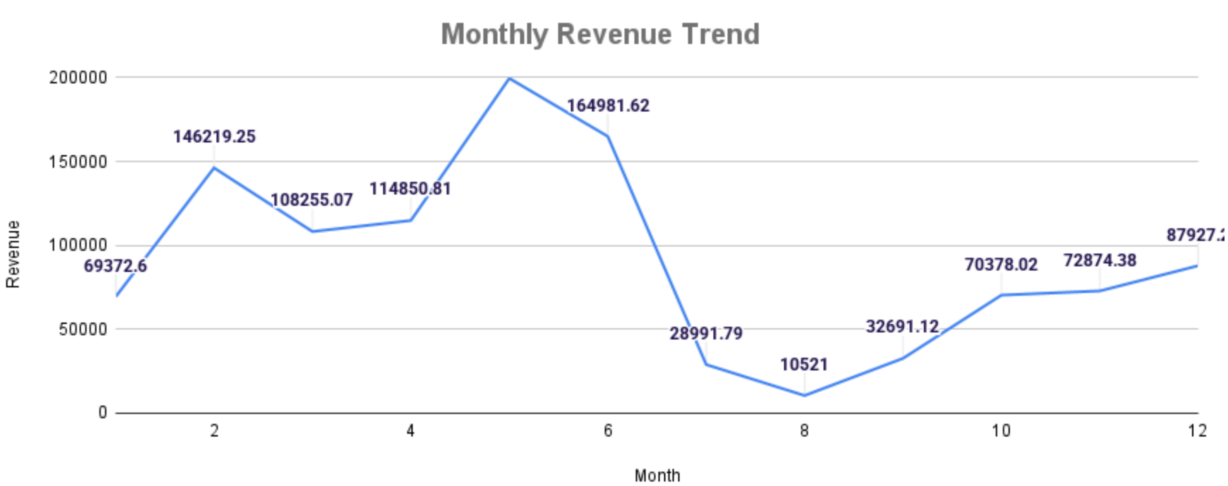


To understand which marketing campaign had the biggest impact on customer engagement, I analyzed the total number of orders generated during each promotional period. The **"Eid Mega Sale"** emerged as the top-performing campaign, bringing in **39 orders**, closely followed by **"Boishakhi Utsob"** with **38 orders**. These results suggest that culturally significant events like Eid and Boishakh drive strong customer interest and purchase activity. Other campaigns like **"Flash Friday Sale"** and **"Ramadan Discount"** also performed well, though to a slightly lesser extent. This insight highlights the importance of aligning promotions with local festivals to maximize sales impact.

```
select
    mc.campaign_name,
    count(distinct o.id) as total_order
from marketing_campaigns as mc
inner join orders as o on mc.id = o.marketing_id
group by 1
order by 2 desc
```

---

7. **What is the revenue trend over days or months?**



To understand SK Mart’s financial performance throughout the year, I analyzed monthly revenue trends using sales data. The analysis revealed clear seasonality and fluctuations.

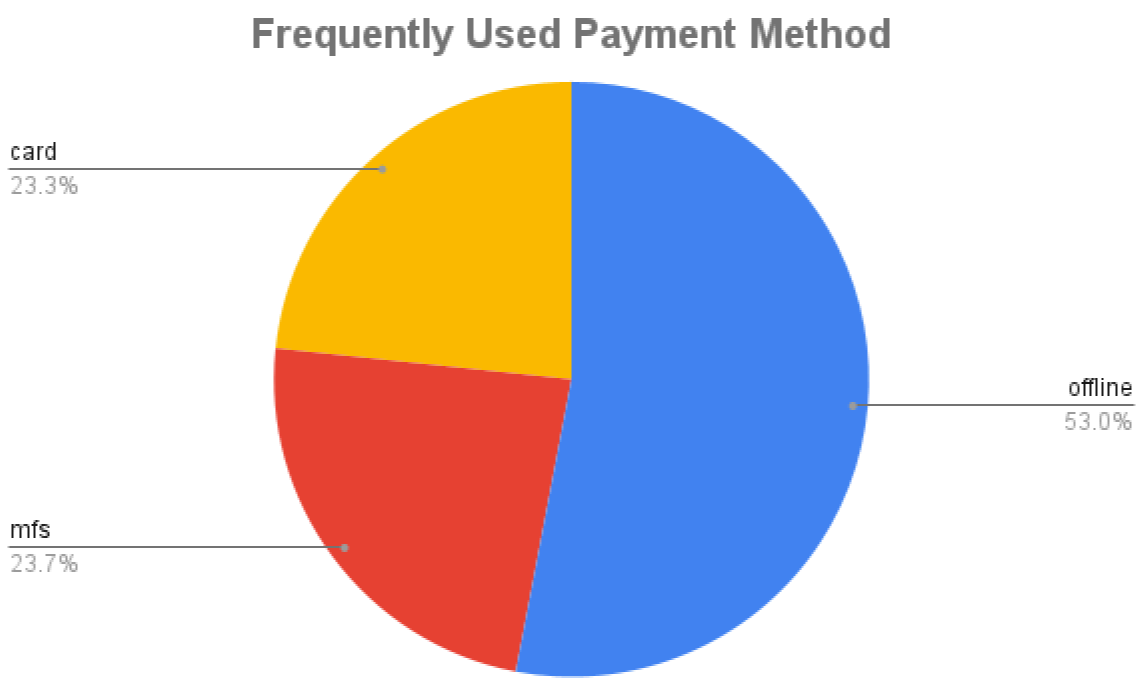
Revenue showed a **steady climb from January**, peaking in **May (৳199,571.73)** — likely influenced by increased consumer activity before Eid or summer campaigns. Following that, **June remained strong**, but there was a sharp **drop in July and August**, suggesting a potential off-season or supply challenges. Towards the end of the year, revenue gradually picked back up, with **consistent performance in October, November, and December**.

This trend indicates that SK Mart experiences **high revenue in pre-festive months** and should consider aligning campaigns and stock planning accordingly.

```
select
  extract(month from o.order_date) as month_,
  sum(oi.quantity * oi.price) as revenue
from orders as o
inner join order_items as oi on o.id = oi.order_id
group by 1
order by 1 asc
```

---

8. **Which payment method is used most frequently?**



To understand customer preferences in transaction behavior, I analyzed all orders placed across SK Mart's retail and online channels. The goal was to identify the most frequently used payment method among options like offline (cash), mobile financial services (MFS), and card payments.

The data revealed a clear preference: **offline payments** (mostly cash on delivery or in-store cash) dominated with **159 transactions**, while **mobile payments (MFS)** and **card transactions** followed closely with **71** and **70** uses respectively. This suggests that although digital payment adoption is growing, a significant portion of SK Mart's customer base still relies on traditional cash payments—highlighting both a cultural preference and an opportunity for digital payment adoption campaigns.

```
select
   payment_method,
   count(payment_method) as used
from orders
group by 1
order by 2 desc;
```

9. **What are the current inventory levels per store and product?**

Store Name	Product Name	Inventory Level
SK Mart Wari	Chanachur	1115
SK Mart Baridhara	Brown Sugar	649
SK Mart Dhanmondi	Soybean Oil	329
SK Mart Uttara	Soybean Oil	608
SK Mart Uttara	Atop Rice	1376
SK Mart Uttara	Gura Chini	496
SK Mart Baridhara	Sunflower Oil	710
SK Mart Tejgaon	Sunflower Oil	1797
SK Mart Baridhara	Chinigura Rice	1276
SK Mart Tejgaon	Mustard Oil	668
SK Mart Dhanmondi	Sunflower Oil	787
SK Mart Wari	Soybean Oil	1578
SK Mart Uttara	Miniket Rice	832
SK Mart Dhanmondi	Atop Rice	1759

To understand current stock availability, I analyzed the inventory levels of each product across SK Mart's retail locations. The results show that products like **Gura Chini**, **Mustard Oil**, and **Chinigura Rice** have high inventory levels, especially in stores like **SK Mart Dhanmondi**, **Tejgaon**, and **Wari**. Notably, **Gura Chini** at Dhanmondi (2,477 units) and **Wari (2,308 units)** are among the highest stock holdings.

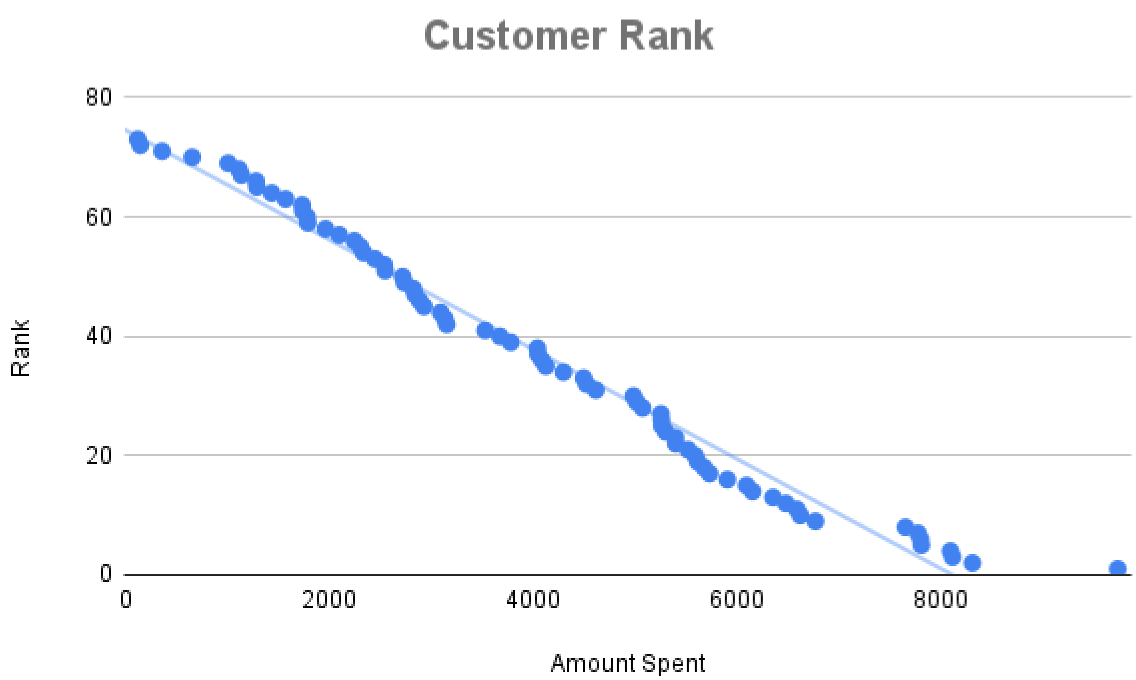
This analysis helps SK Mart monitor inventory distribution across stores and identify overstocked or understocked items for better inventory planning and store-level replenishment decisions.

```
select
    s.store_name,
```

```
    p.name,
    sum(i.quantity) as inventory_level
from inventory as i
inner join stores as s on s.id = i.store_id
inner join products as p on p.id = i.product_id
group by 1, 2;
```

---

10. **Rank customers by total amount spent.**



To understand customer value and purchasing behavior, I ranked all customers based on their total amount spent at SK Mart. The analysis revealed that **Jayesh Lall** is the highest spender with a total of **৳9,729.33**, followed by **Aradhya Lall** and **Kimaya Bose**, spending **৳8,302.81** and **৳8,107.54** respectively. The top 10 customers contribute significantly to overall sales, highlighting key individuals for potential loyalty rewards or targeted marketing initiatives.

```
select
    c.full_name,
    sum(o.total_amount) as amount_spend,
    rank() over(order by sum(o.total_amount) desc) as customer_rank
from customers as c
inner join orders as o on c.id = o.customer_id
group by 1;
```

---

11. **Show the top 3 best-selling products per store.**

Store Name	Product	Rank
SK Mart Azimpur	Chili Powder	1
SK Mart Azimpur	Nimki	2
SK Mart Azimpur	White Sugar	3
SK Mart Azimpur	Detergent	3
SK Mart Azimpur	Turmeric Powder	3
SK Mart Banani	Cheese	1
SK Mart Banani	White Sugar	2
SK Mart Banani	Onion	3
SK Mart Banani	Turmeric Powder	3
SK Mart Baridhara	Yogurt	1
SK Mart Baridhara	Sunflower Oil	2
SK Mart Baridhara	Chili Powder	3
SK Mart Dhanmondi	Coca Cola	1
SK Mart Dhanmondi	Turmeric Powder	1
SK Mart Dhanmondi	Soybean Oil	1
SK Mart Gulshan	Bread	1
SK Mart Gulshan	Chili Powder	2
SK Mart Gulshan	Sprite	2
SK Mart Lalmatia	Coca Cola	1
SK Mart Lalmatia	Brown Sugar	2
SK Mart Lalmatia	Gura Chini	3

To identify product demand at the store level, I analyzed the sales data to extract the
top 3 best-selling products per SK Mart outlet. The analysis revealed that **product preferences vary significantly by location**. For instance, **Chili Powder**

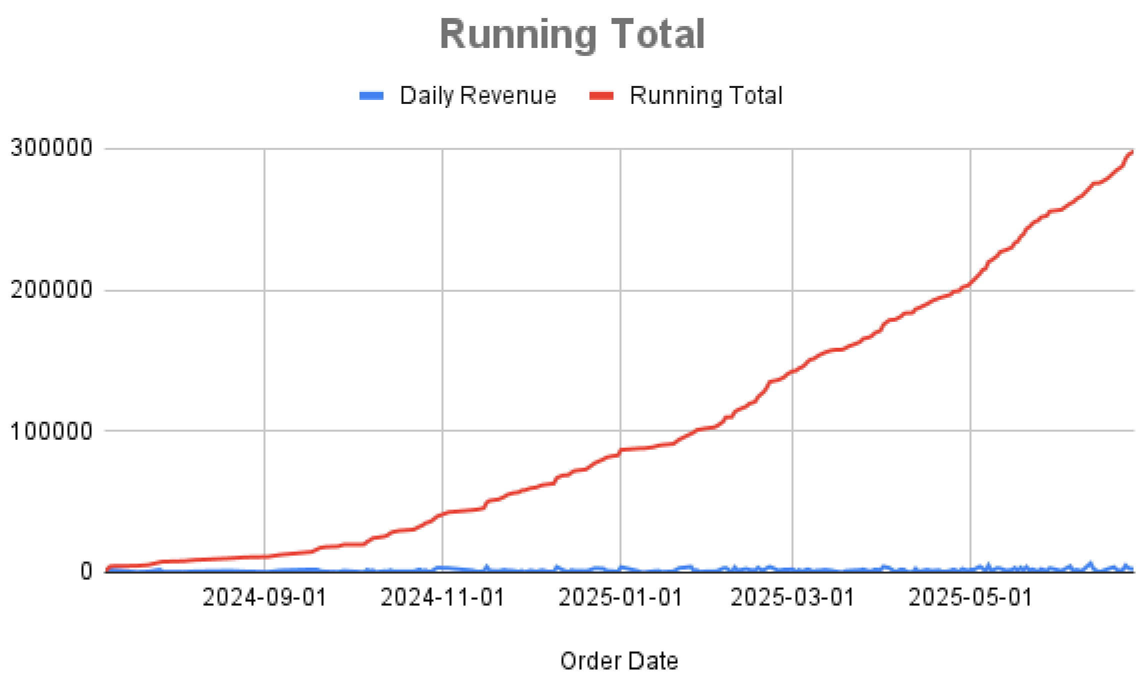
performed consistently well in multiple branches like Azimpur and Gulshan, while **Coca Cola** ranked among the top choices in Dhanmondi, Lalmatia, and Tejgaon. Additionally, **dairy and beverage items** such as **Milk**, **Yogurt**, and **Cheese** appeared frequently in the top ranks across different areas, indicating high customer demand. These insights can guide SK Mart's inventory stocking and promotional strategies based on location-specific preferences.

```
with top_3_product as(
select
    s.store_name,
    p.name,
    sum(oi.quantity) as sold,
    rank() over(partition by s.store_name order by sum(oi.quantity) desc ) as rank_
from products as p
inner join order_items as oi on p.id = oi.product_id
inner join orders as o on oi.order_id = o.id
inner join stores as s on s.id = o.store_id
group by 1, 2
)

select *
from top_3_product
where rank_ <= 3;
```

---

12. **Calculate a running total of daily revenue.**

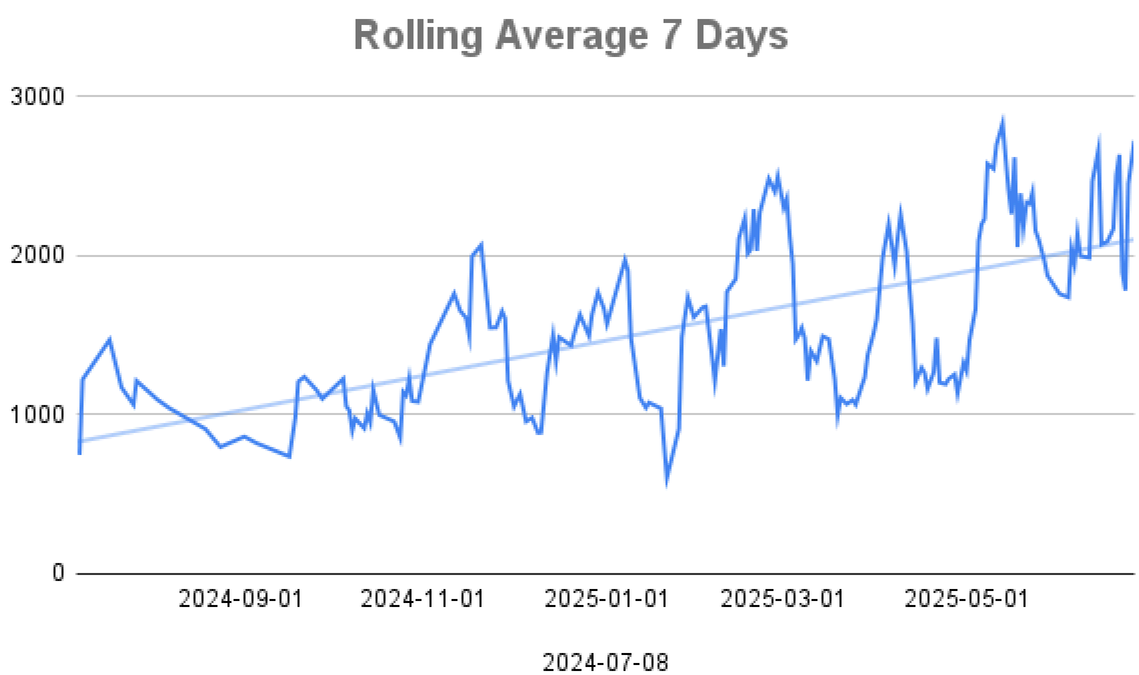


To understand how daily revenue is accumulating over time, I calculated a **running total of daily revenue**. This analysis helps visualize the business's revenue growth trajectory across different months.

From **July 8, 2024** to **June 26, 2025**, SK Mart generated a total revenue of **৳298,027.73**. The revenue trend shows consistent daily sales with noticeable spikes on certain days, indicating high-performing dates or successful marketing efforts. This running total helps in identifying sales momentum, tracking monthly performance, and forecasting future revenue potential.

```
select
    date(created_at) as order_date,
    sum(price) as daily_revenue,
    sum(sum(price)) over(order by date(created_at)) as runnig_total_revenue
from order_items
group by 1
order by 1;
```

13. **Compute a 7-day rolling average of total order amounts.**



To understand the trend of customer spending over time, I computed a **7-day rolling average** of total order amounts. This helped smooth out daily fluctuations and reveal the underlying sales momentum for SK Mart.

Early in the timeline (July to September 2024), average order values hovered around **৳800–৳1,200**, indicating modest daily sales volumes. However, from **November onward**, the rolling average began climbing steadily — peaking above **৳2,500** in May and June 2025. This sharp rise signals a period of **sustained high sales**, possibly influenced by effective marketing campaigns, seasonal demand, or promotional offers.

Notably, the highest spikes occurred between **late May and late June**, suggesting a successful promotional period or festival-related demand surge. This insight can help SK Mart align future campaigns with these high-performing windows to maximize revenue.

```
with daily_order_totals as (
select
   date(created_at) as order_date,
   sum(price) as daily_revenue
from order_items
group by 1
),
rolling_avg as(
select
   order_date,
   daily_revenue,
   round(avg(daily_revenue) over(order by order_date rows between 6 preceding
from daily_order_totals
)
select *
from rolling_avg
order by 1;
```

---

14. **Show the time difference between each customer's consecutive orders.**

Customer Name	Current Order Date	Previous Order Date	Time difference
Aarush Batta	2025-01-28	2024-07-27	185 days
Aarush Batta	2025-01-30	2025-01-28	2 days
Aarush Batta	2025-02-26	2025-01-30	27 days
Aarush Batta	2025-04-01	2025-02-26	34 days
Aarush Batta	2025-06-01	2025-04-01	61 days
Aaryahi Agrawal	2024-12-20	2024-09-19	92 days
Aaryahi Agrawal	2025-02-10	2024-12-20	52 days
Aaryahi Agrawal	2025-03-08	2025-02-10	26 days
Aaryahi Agrawal	2025-03-27	2025-03-08	19 days
Adah Sur	2025-04-07	2024-11-11	147 days
Advik Kaul	2025-02-19	2025-01-15	35 days
Advik Kaul	2025-04-20	2025-02-19	60 days
Advik Korpal	2024-12-31	2024-10-05	87 days
Advik Korpal	2025-03-16	2024-12-31	75 days
Amira Kamdar	2025-01-21	2025-01-14	7 days
Amira Kamdar	2025-03-03	2025-01-21	41 days

Understanding how frequently customers return to shop is crucial for any retail business aiming to boost retention and optimize marketing efforts. In this analysis, I calculated the time difference between each customer's consecutive orders to uncover individual buying patterns.

For instance, **Aarush Batta** showed a fairly regular shopping habit, with intervals ranging from just **2 days** to **61 days**, while **Aaryahi Agrawal** had slightly more spread-out purchases, averaging **30–50 days** between orders. Some customers, like **Darshit Vig**, returned every **15–30 days**, indicating strong engagement, whereas others, such as **Mamooty Yadav**, had a much longer gap of **255 days** between visits—suggesting either a seasonal buyer or churn risk.

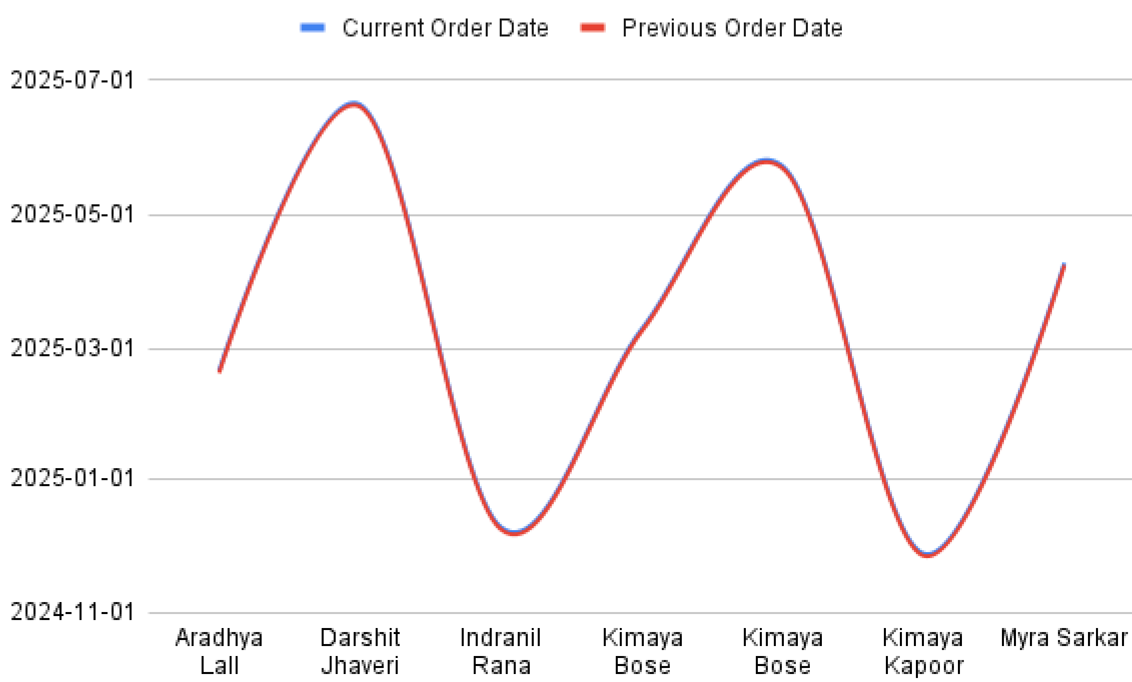
These findings highlight clear differences in shopping behavior across the customer base. By identifying frequent buyers, SK Mart can personalize offers and loyalty programs. On the other hand, customers with long gaps between orders can be targeted with re-engagement campaigns via SMS or email.

This analysis lays the groundwork for building **customer segmentation models** based on recency and frequency, a key step toward more targeted and effective marketing strategies.

```
with time_diff as(
select
  c.full_name as full_name,
  o.id as current_order_id,
  date(o.created_at) as current_order_date,
  lag(date(o.created_at)) over (partition by c.full_name order by o.created_at) as p
  o.created_at - lag(o.created_at) over (partition by c.full_name order by o.createc
from orders as o
inner join customers as c on c.id = o.customer_id
order by c.full_name, o.created_at
)
select *
from time_diff
where time_diff is not null;
```

---

15. Identify customers who placed two orders on back-to-back days.



While analyzing SK Mart's order history, I explored customer purchase patterns to identify loyal or highly engaged buyers. One interesting discovery was a group of customers who placed orders on **consecutive days** — a strong signal of consistent need or satisfaction with the service.

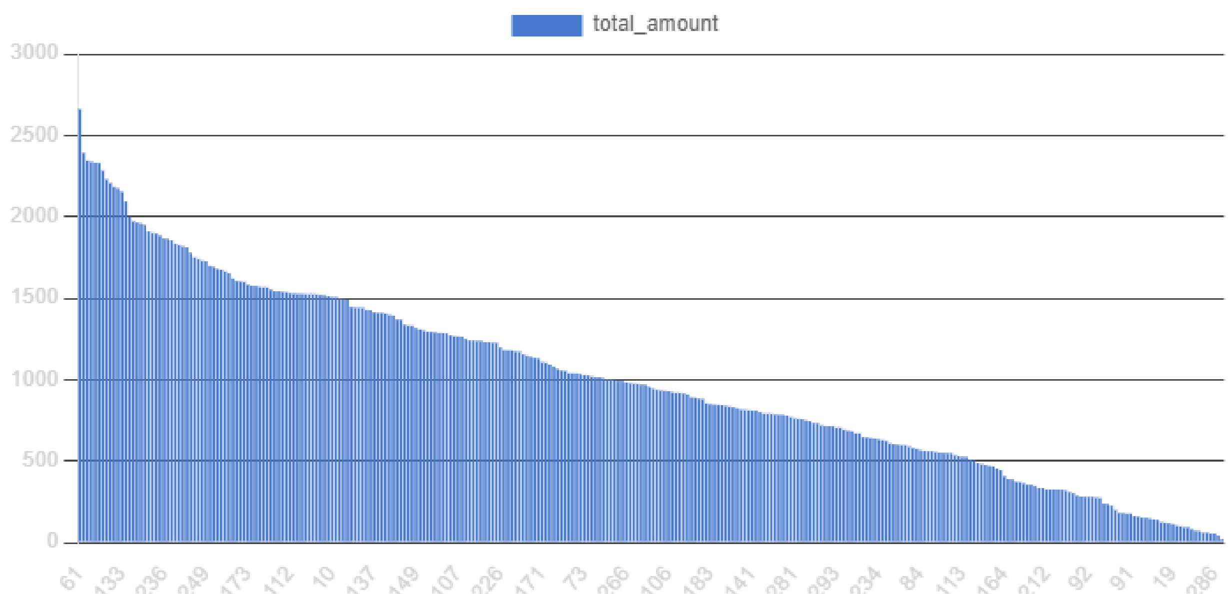
The analysis revealed **7 such instances**, involving repeat buyers like **Kimaya Bose**, who made back-to-back purchases not just once, but twice. Other customers like **Aradhya Lall**, **Darshit Jhaveri**, and **Myra Sarkar** also placed orders on the very next day, indicating urgency or habitual shopping behavior.

This insight highlights an opportunity for SK Mart to explore customer segmentation for **frequent buyers**, potentially offering them personalized promotions, loyalty perks, or subscription-based delivery models.

```
with time_dif as(
select
  c.full_name as full_name,
  o.id as current_order_id,
  date(o.created_at) as current_order_date,
```

```
  lag(date(o.created_at)) over (partition by c.full_name order by o.created_at) as p
  o.created_at - lag(o.created_at) over (partition by c.full_name order by o.createc
from orders as o
inner join customers as c on c.id = o.customer_id
)
select *
from time_dif
where  current_order_date - previous_order_date = 1
order by 1, 2;
```

16. **Classify orders as ‘High’, ‘Medium’, or ‘Low’ value based on amount.**



To better understand customer spending behavior, I classified each order placed at SK Mart into three categories: **High**, **Medium**, or **Low** value—based on the total amount spent per order.

The analysis revealed that a significant portion of SK Mart's revenue is driven by a relatively small number of **High-value orders**, typically exceeding ৳1,500. These orders often include bulk purchases or multiple high-priced items. Customers placing such orders represent strong sales opportunities and should be considered for loyalty or premium marketing campaigns.

On the other hand, the **majority of orders** fall into the **Medium** category, indicating consistent day-to-day purchases of regular household goods. These customers are likely returning buyers who form the core of SK Mart's customer base.

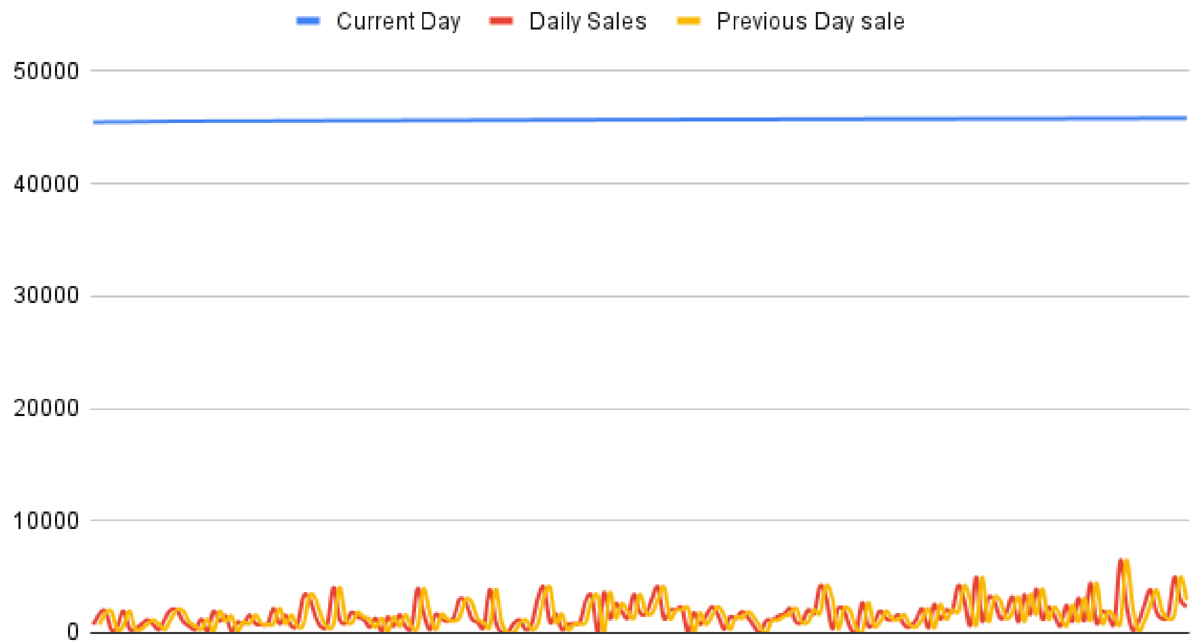
Finally, **Low-value orders** made up a smaller share of the total. These may represent first-time buyers, emergency purchases, or price-sensitive customers. Targeting this group with personalized offers or bundled deals could help increase average order value.

This classification not only helps SK Mart segment its customers better but also enables smarter inventory planning and campaign targeting based on customer purchase behavior.

```
select
    id,
    total_amount,
    case
        when total_amount <= 500 then 'Low'
        when total_amount between 500 and 1500 then 'Medium'
        when total_amount >= 1500 then 'High'
        else 'Undefined'
    end as order_category
from orders
order by 2 desc;
```

---

17. **Show whether each day's sales were higher or lower than the previous day.**



To understand daily sales momentum, I analyzed whether each day's revenue was higher or lower than the previous day. The trend revealed a fluctuating sales pattern without a consistent upward or downward trajectory. Periods of sharp spikes—like those on **January 1, February 6, and June 11**—were often followed by steep drops, suggesting possible campaign effects or stock-driven surges. Conversely, several multi-day downward streaks also occurred, potentially signaling off-peak periods or low inventory days.

This analysis helps SK Mart identify not just high and low revenue days, but also **sales volatility**, which can guide better inventory planning, campaign timing, and promotional strategies for more stable growth.

```
with current_day_sales as(
select
   date(created_at) as current_day,
   sum(price) as daily_sales
from order_items
group by 1
),
```

```
previous_day as(
select
    current_day,
    daily_sales,
    lag(daily_sales) over(order by current_day) as previou_day_sale
from current_day_sales
)


select
    current_day,
    daily_sales,
    previou_day_sale,
    case
        when previou_day_sale is null then 'No previous data'
        when previou_day_sale > daily_sales then 'Lower'
        when previou_day_sale < daily_sales then 'Higher'
        else 'Same'
    end as sales_trend,
    daily_sales - previou_day_sale as diff
from previous_day
order by 1;
```

---

18. **Find customers who placed only one order ever.**

"Badal Rattan"
"Elakshi Kumer"
"Hridaan Yohannan"
"Kaira Chowdhury"
"Madhup Dasgupta"
"Sana Wali"

During the analysis, I explored customer engagement to identify individuals who placed only **one order ever** at SK Mart. This kind of insight helps in understanding customer retention and loyalty challenges.

From the data, I found that **six customers** — including **Badal Rattan**, **Elakshi Kumer**, and **Sana Wali** — made just a **single purchase** and never returned. These one-time buyers may indicate gaps in customer experience, lack of follow-up marketing, or product dissatisfaction. Understanding why these customers didn't come back could help SK Mart improve its retention strategy and customer lifetime value.

```
with order_details as (
select
   c.full_name,
   count( distinct o.id) as order_
from customers as c
inner join orders as o on c.id = o.customer_id
group by 1
)
select *
from order_details
where order_ = 1;
```

---

19. **Find products that were only ordered during marketing campaigns.**

To understand the direct impact of SK Mart's marketing efforts, I explored which products were **exclusively purchased during marketing campaign periods—** meaning they were never ordered outside those campaigns.

Through SQL analysis, I identified several items that were tightly linked to specific campaigns. For example, products like **"Onion," "Yogurt," "Cheese," "Chinigura Rice,"** and **"Frooti"** appeared consistently across multiple campaign events like *Boishakhi Utsob*, *Eid Mega Sale*, and *Ramadan Discount*, but were never ordered outside these periods.

This pattern suggests that these products likely benefited from:

- **Special pricing**, **bundles**, or **highlighted promotions** during campaigns
- **Impulse purchases** influenced by campaign visibility (e.g., Facebook or offline banners)

Interestingly, items like **Mountain Dew**, **Chanachur**, **Gura Chini**, and **Toilet Cleaner** also made repeat appearances, indicating that SK Mart's promotional timing and product mix were effective in creating **temporary demand surges**.

From a business perspective, this insight helps SK Mart:

- Identify **campaign-dependent products**
- Plan inventory more precisely around promotional periods
- Decide which products could benefit from year-round availability or continued marketing push

In short, the data reveals that **campaigns not only boosted visibility** but also drove **exclusive buying behavior** for certain fast-moving consumer goods.

```
select
   p.name,
   mc.campaign_name
from order_items as oi
inner join products as p on p.id = oi.product_id
inner join orders as o on o.id = oi.order_id
inner join marketing_campaigns as mc on mc.id = o.marketing_id;
```

---

20. **Find the most popular product among buyers of 'Soybean Oil'.**

To better understand customer buying behavior, I explored what other products are frequently purchased by customers who buy **Soybean Oil**. This type of basket analysis helps identify cross-selling opportunities and product affinities.

After analyzing the purchase patterns, the result revealed a clear trend — **"Milk"** emerged as the **most popular product** among Soybean Oil buyers, with **14**

purchases. This insight suggests that customers often bundle these daily essentials together, possibly during routine grocery shopping. SK Mart can use this pattern to create targeted combos, promotions, or shelf placements to boost basket size and overall sales.

```
WITH soybean_oil_buyers AS (
    SELECT DISTINCT c.id AS customer_id
    FROM customers c
    JOIN orders o ON c.id = o.customer_id
    JOIN order_items oi ON o.id = oi.order_id
    JOIN products p ON oi.product_id = p.id
    WHERE p.name = 'Soybean Oil'
),


customer_other_products AS (
    SELECT
        p.name AS product_name,
        COUNT(*) AS purchase_count
    FROM customers c
    JOIN orders o ON c.id = o.customer_id
    JOIN order_items oi ON o.id = oi.order_id
    JOIN products p ON oi.product_id = p.id
    WHERE c.id IN (SELECT customer_id FROM soybean_oil_buyers)
      AND p.name <> 'Soybean Oil'
    GROUP BY p.name
)


SELECT product_name, purchase_count
FROM customer_other_products
ORDER BY purchase_count DESC
LIMIT 1;
```

Check out complete project on **Github**

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