CODE BASIC DATA CHALLENGE

Providing Insights for Crisis Recovery in an Online Food Delivery Startup

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Analyzed QuickBite's operational and customer data to uncover factors behind order decline, delivery inefficiencies, and customer churn during the 2025 crisis; developed data-driven insights and predictive models to support recovery planning, using Python and Machine Learning.

Introduction

This project presents a comprehensive data-driven analysis of **QuickBite**, a Bengaluru-based food delivery startup that experienced a major operational and reputation crisis in mid-2025. The incident, triggered by viral food safety concerns and delivery disruptions, led to a sharp decline in customer engagement, order volumes, and overall satisfaction.

To support QuickBite's recovery strategy, this analysis was carried out using **Python (Pandas, NumPy, Seaborn, Matplotlib, and Scikit-learn)** to explore, clean, and model multiple datasets covering customers, restaurants, orders, delivery performance, and customer feedback. The study focuses on comparing business performance across two distinct phases — **Pre-Crisis (January to May 2025)** and **Crisis (June to September 2025)** — to measure the impact on key business metrics.

Project Workflow

The project workflow included:

- **Data loading and preprocessing:** importing CSV files, cleaning timestamps, merging tables, and creating time-based "phase" segments.
- **Exploratory analysis:** evaluating trends in monthly orders, cancellations, delivery SLAs, and ratings.
- **Sentiment analysis:** extracting negative keywords from crisis-period reviews to identify customer pain points.
- **Revenue and loyalty impact assessment:** estimating financial losses and identifying churned loyal customers.
- **Predictive modeling:** applying machine learning techniques to forecast churn, SLA compliance, and high-value order patterns.

Through this structured analysis, the project delivers actionable insights into customer behavior, delivery efficiency, and sentiment trends, helping QuickBite's management design data-backed initiatives for service improvement and brand trust rebuilding.

Understanding & Preview Of Dataset

- **dim_customer.csv –** Contains customer-level details such as customer_id, signup_date, city, and acquisition_channel, used to analyze user demographics and acquisition trends.
- **dim_delivery_partner.csv –** Includes information on delivery partners like partner_name, city, vehicle_type, employment_type, and avg_rating, helping assess delivery performance and workforce mix.

```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter
import re
import numpy as np


# Loading Dataset

df_customer = pd.read_csv("/content/dim_customer.csv")
df_customer.head()
```

	customer_id	signup_date	city	acquisition_channel
0	CUST000007	21-03-2025	Pune	Organic
1	CUST000008	07-02-2025	Kolkata	Referral
2	CUST000009	25-02-2025	Delhi	Paid
3	CUST000010	28-01-2025	Hyderabad	Paid
4	CUST000011	18-01-2025	Kolkata	Organic

```python
df_delivery_partner = pd.read_csv("/content/dim_delivery_partner_.csv")
df_delivery_partner.head()
```

	delivery_partner_id	partner_name	city	vehicle_type	employment_type	avg_rating	is_active
0	DP09615	Neha E	Bengaluru	Scooter	Full-time	3.77	Y
1	DP02021	Neha V	Bengaluru	Bike	Full-time	3.90	Y
2	DP05541	Vikas S	Delhi	Cycle	Part-time	3.33	Y
3	DP13859	Amit B	Delhi	Cycle	Part-time	4.07	N
4	DP08091	Arjun R	Mumbai	Car	Full-time	4.63	Y

- **dim_menu_item.csv** – Lists restaurant menu items with fields such as `menu_item_id`, `item_name`, `category`, `is_veg` and `price`, enabling pricing and item-level order analysis.

- **dim_restaurant.csv** – Contains restaurant-related attributes including `restaurant_id`, `restaurant_name`, `city`, `cuisine_type`, `partner_type`, and `avg_prep_time_min`, used for location and cuisine performance evaluation.

- **fact_orders.csv** – Core transactional dataset with details like `order_id`, `customer_id`, `restaurant_id`, `order_timestamp`, `subtotal_amount`, and `is_cancelled`, forming the base for order trend and cancellation analysis.

```
df_menu_item = pd.read_csv("/content/dim_menu_item.csv")
df_menu_item.head()
```

	menu_item_id	restaurant_id	item_name	category	is_veg	price
0	MENU12962_3216	REST12962	Paneer Tikka Pizza	Pizza	Y	271.05
1	MENU12962_1962	REST12962	Pepperoni Pizza	Pizza	N	327.26
2	MENU14069_0510	REST14069	Egg Fried Rice	Fried Rice	N	200.01
3	MENU14069_4308	REST14069	Paneer Tikka	Starters	Y	198.83
4	MENU08622_7574	REST08622	Kadai Paneer	Curries	Y	271.60

```
df_restaurant = pd.read_csv("/content/dim_restaurant.csv")
df_restaurant.head()
```

	restaurant_id	restaurant_name	city	cuisine_type	partner_type	avg_prep_time_min	is_active
0	REST12962	Flavours of Sweets Palace	Bengaluru	Chinese	Restaurant	26-40	N
1	REST14069	Royal Biryani Darbar	Ahmedabad	Fast Food	Restaurant	16-25	Y
2	REST08622	Spicy Wraps Point	Mumbai	North Indian	Restaurant	16-25	Y
3	REST19745	Delhi Express Palace	Ahmedabad	Pizza	Cloud Kitchen	16-25	Y
4	REST02383	Namma Mess Delight	Mumbai	Healthy	Restaurant	26-40	Y

```
df_delivery_performance = pd.read_csv("/content/fact_delivery_performance.csv")
df_delivery_performance.head()
```

	order_id	actual_delivery_time_mins	expected_delivery_time_mins	distance_km
0	ORD202501023439	31	31	6.4
1	ORD202501012051	46	42	1.9
2	ORD202501019281	25	31	6.2
3	ORD202501000124	29	41	6.2
4	ORD202501006518	37	41	2.4

- **fact_order_items.csv** – Captures order-level item details (`item_id, menu_item_id, quantity, unit_price, item_discount`), helping calculate total bill values and discount impacts.

- **fact_delivery_performance.csv** – Tracks delivery metrics such as `actual_delivery_time_mins, expected_delivery_time_mins`, and `distance_km`, used to measure SLA compliance and delivery delays.

- **fact_ratings.csv** – Includes post-delivery feedback with `rating, review_text, review_timestamp`, and `sentiment_score`, supporting customer satisfaction and sentiment analysis.

```
df_order_items = pd.read_csv("/content/fact_order_items.csv")
df_order_items.head()
```

	order_id	item_id	menu_item_id	restaurant_id	quantity	unit_price	item_discount	line_total
0	ORD202501006518	ITEM001	MENU12962_3216	REST12962	2	48.31	0.00	96.62
1	ORD202501006518	ITEM002	MENU12962_1962	REST12962	3	61.24	0.00	183.71
2	ORD202501019281	ITEM001	MENU14069_0510	REST14069	2	87.19	0.00	174.38
3	ORD202501019281	ITEM002	MENU14069_4308	REST14069	3	84.67	0.00	254.00
4	ORD202501023439	ITEM001	MENU08622_7574	REST08622	2	235.81	35.44	436.18

```
df_orders = pd.read_csv("/content/fact_orders.csv")
df_orders.head()
```

	order_id	customer_id	restaurant_id	delivery_partner_id	order_timestamp	subtotal_amount	discount_amount	delivery_fee	total_amount	is_cod	is_cancelled
0	ORD202501023439	CUST181110	REST08622	DP05541	2025-01-01 12:00:00	471.62	35.44	30.56	466.74	N	N
1	ORD202501012051	CUST025572	REST02383	DP08091	2025-01-01 12:00:00	255.68	0.00	27.45	283.13	Y	N
2	ORD202501019281	CUST179306	REST14069	DP02021	2025-01-01 12:00:00	428.38	0.00	26.23	454.61	N	N
3	ORD202501000124	CUST191820	REST19745	DP13859	2025-01-01 12:00:00	260.81	0.00	32.75	293.56	N	N
4	ORD202501006518	CUST033760	REST12962	DP09615	2025-01-01 12:00:00	280.33	0.00	25.57	305.90	N	N

```
fact_ratings = pd.read_csv("/content/fact_ratings.csv")
fact_ratings.head()
```

	order_id	customer_id	restaurant_id	rating	review_text	review_timestamp	sentiment_score
0	ORD202501023439	CUST181110	REST08622	4.5	Super fast delivery	01-01-2025 15:00	0.75
1	ORD202501019281	CUST179306	REST14069	4.5	Great taste!	01-01-2025 15:00	0.75
2	ORD202501018036	CUST093042	REST13907	5.0	Super fast delivery	01-01-2025 14:03	1.00
3	ORD202501007724	CUST110825	REST08451	4.0	Tasty but a bit late	01-01-2025 14:06	0.50
4	ORD202501002349	CUST181669	REST00225	4.4	Satisfied overall	01-01-2025 14:06	0.70

Data Preprocessing

The following steps were performed to clean, transform, and prepare the datasets for analysis:

- **Timestamp Conversion:**
  All date and time fields were converted from text to proper datetime format to enable time-based calculations and visualizations.

```
# Prepare df_orders: Convert timestamp and define phase
df_orders['order_timestamp'] = pd.to_datetime(df_orders['order_timestamp'])
df_orders['order_date'] = df_orders['order_timestamp'].dt.date
df_orders['phase'] = df_orders['order_date'].apply(
    lambda x: 'Crisis' if x >= pd.to_datetime(CRISIS_START_DATE).date() else 'Pre-Crisis'
)
```

- **Date and Month Extraction:**
  Separate columns were created for order date and order month to support monthly trend analysis and comparison across business phases.

```
# Define the strict periods for consistency across Q1-Q9:
PRE_CRISIS_START = pd.to_datetime('2025-01-01').date()
PRE_CRISIS_END = pd.to_datetime('2025-05-31').date()
CRISIS_START = pd.to_datetime('2025-06-01').date()
CRISIS_END = pd.to_datetime('2025-09-30').date()
```

- **Phase Definition:**
  The timeline was divided into two distinct phases — **Pre-Crisis (January–May 2025)** and **Crisis (June–September 2025)**.
  Each order record was tagged accordingly to allow consistent phase-wise analysis.

```
def define_phase(date):
    if PRE_CRISIS_START <= date <= PRE_CRISIS_END:
        return 'Pre-Crisis'
    elif CRISIS_START <= date <= CRISIS_END:
        return 'Crisis'
    return 'Other'

df_orders['phase'] = df_orders['order_date'].apply(define_phase)
# Filter down to only the relevant analysis periods for all Qs (1-9)
analysis_df = df_orders[df_orders['phase'] != 'Other'].copy()
```

- **Review Data Cleaning:**
  The review dataset was standardized by converting review timestamps to datetime, removing invalid or missing records, and creating a monthly grouping column for trend analysis.

```
# Prepare df_ratings: Convert timestamp and define month
fact_ratings['review_timestamp'] = pd.to_datetime(fact_ratings['review_timestamp'], format='%d-%m-%Y %H:%M', errors='coerce')
fact_ratings = fact_ratings.dropna(subset=['review_timestamp', 'rating']).copy()
fact_ratings['review_month'] = fact_ratings['review_timestamp'].dt.to_period('M')
```

- **City Information Merge:**
  City details from the restaurant dataset were merged with the order data to enable city-level performance insights such as order decline, cancellations, and revenue variation.

```
# Merge City information for Orders (used in Q2, Q4)
orders_with_city = analysis_df.merge(
    df_restaurant[['restaurant_id', 'city']],
    on='restaurant_id',
    how='left'
)
```

- **Filtering Relevant Periods:**
  Data outside the defined Pre-Crisis and Crisis timeframes was excluded to maintain focus on the analysis period of interest.

```
df_orders['phase'] = df_orders['order_date'].apply(define_phase)
# Filter down to only the relevant analysis periods for all Qs (1-9)
analysis_df = df_orders[df_orders['phase'] != 'Other'].copy()
```

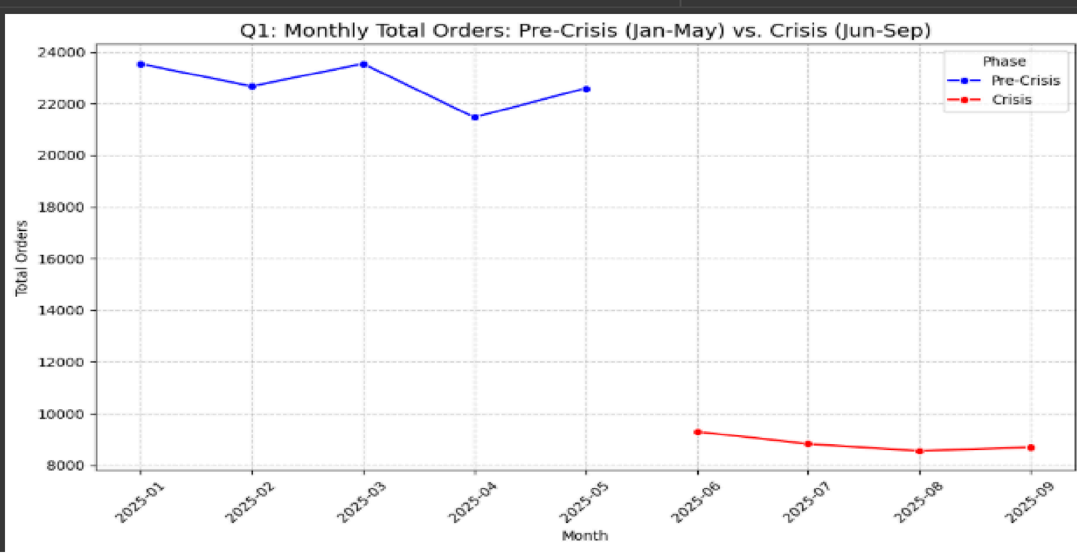
These preprocessing steps ensured that the data was accurate, well-structured, and aligned across all dimensions for reliable and meaningful analysis.

Primary Analysis

Q1. Monthly Orders Trend and Decline Severity

- **Objective:** Measure total order decline between Pre-Crisis and Crisis periods.
- **Approach:** Aggregated monthly order counts using `groupby(['order_month', 'phase'])` and visualized with Seaborn line plots.
- **Result:** Orders dropped from **113,806 (Pre-Crisis)** to **35,360 (Crisis)** — a **69% decline**.
- **Insight:** Confirms severe drop in user activity immediately after the food safety incident.

```python
# Q1. Monthly Orders Trend and Decline Severity
# ====================================================

# Calculate Monthly Orders
monthly_orders = analysis_df.groupby(['order_month', 'phase'])['order_id'].count().reset_index()
monthly_orders['month_str'] = monthly_orders['order_month'].astype(str)
monthly_orders.rename(columns={'order_id': 'Total Orders'}, inplace=True)

# Calculate Total Orders by Phase and Decline Percentage
total_orders_by_period = analysis_df.groupby('phase')['order_id'].count()
pre_crisis_orders = total_orders_by_period.get('Pre-Crisis', 0)
crisis_orders = total_orders_by_period.get('Crisis', 0)

if pre_crisis_orders > 0:
    decline_percentage = ((pre_crisis_orders - crisis_orders) / pre_crisis_orders) * 100
else:
    decline_percentage = 0

# Visualization (Q1)
plt.figure(figsize=(10, 6))
sns.lineplot(x='month_str', y='Total Orders', hue='phase', data=monthly_orders, marker='o', palette={'Pre-Crisis': 'blue', 'Crisis': 'red'})
plt.title('Q1: Monthly Total Orders: Pre-Crisis (Jan-May) vs. Crisis (Jun-Sep)', fontsize=14)
plt.xlabel('Month')
plt.ylabel('Total Orders')
plt.xticks(rotation=45)
plt.grid(True, linestyle='--', alpha=0.6)
plt.legend(title='Phase')
plt.tight_layout()
plt.show()
```



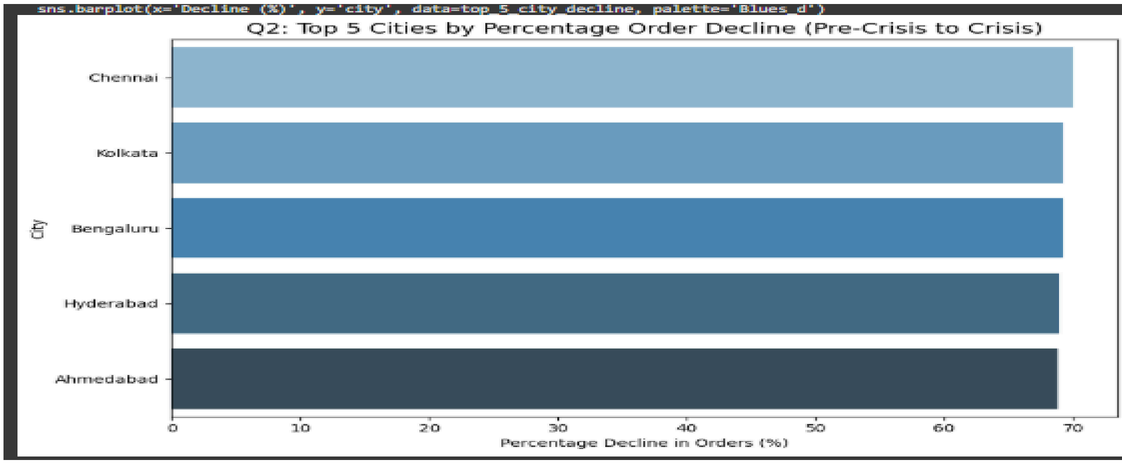
Q2. Top 5 City Decline

Objective: Identify cities with the highest drop in orders during the crisis.
Approach: Calculated order counts by city and phase using grouped aggregation.
Result: Chennai, Kolkata, Bengaluru, Hyderabad, and Ahmedabad saw ~70% order decline.
Insight: Tier-1 cities were most affected, indicating strong public reaction and market sensitivity.

```
# Q2. Top 5 City Decline
# ====================================================

# Calculate orders by city and phase
city_orders = orders_with_city.groupby(['city', 'phase'])['order_id'].count().unstack(fill_value=0)
city_orders.columns = ['Crisis Orders', 'Pre-Crisis Orders']

# Filter for cities with non-zero pre-crisis orders
city_orders = city_orders[city_orders['Pre-Crisis Orders'] > 0].copy()

# Calculate percentage decline
city_orders['Decline (%)'] = (
    (city_orders['Pre-Crisis Orders'] - city_orders['Crisis Orders']) /
    city_orders['Pre-Crisis Orders']
) * 100

# Top 5 decline
top_5_city_decline = city_orders.sort_values('Decline (%)', ascending=False).head(5).reset_index()

# Print the actual data output before visualization
print("Top 5 Cities by Percentage Order Decline (Pre-Crisis vs Crisis):\n")
print(top_5_city_decline.to_string(index=False))

# Visualization (Q2)
plt.figure(figsize=(9, 6))
sns.barplot(x='Decline (%)', y='city', data=top_5_city_decline, palette='Blues_d')
plt.title('Q2: Top 5 Cities by Percentage Order Decline (Pre-Crisis to Crisis)', fontsize=14)
plt.xlabel('Percentage Decline in Orders (%)')
plt.ylabel('City')
plt.tight_layout()
plt.show()
```

```
Top 5 Cities by Percentage Order Decline (Pre-Crisis vs Crisis):

     city  Crisis Orders  Pre-Crisis Orders  Decline (%)
  Chennai           3463              11537    69.983531
  Kolkata           3226              10470    69.188157
Bengaluru           8700              28219    69.169708
Hyderabad           3589              11546    68.915642
Ahmedabad           2916               9355    68.829503
/tmp/ipython-input-3352825359.py:26: FutureWarning:
```

```
sns.barplot(x='Decline (%)', y='city', data=top_5_city_decline, palette='Blues_d')
```



Q3. Restaurant Decline

Objective: Find top 10 high-volume restaurants with major order decline.

Approach: Filtered restaurants with ≥50 pre-crisis orders and compared order volumes.

Result: All key restaurants reported >60% decline with no positive performers.

Insight: Trust erosion was widespread across restaurant partners, not limited to specific outlets.

```python
# Q3. Top 10 High-Volume Restaurant Decline

restaurant_orders = analysis_df.groupby(['restaurant_id', 'phase'])['order_id'].count().unstack(fill_value=0)
restaurant_orders.columns = ['Crisis Orders', 'Pre-Crisis Orders']

high_volume_restaurants = restaurant_orders[restaurant_orders['Pre-Crisis Orders'] >= 50].copy()
high_volume_restaurants['Decline (%)'] = (
    (high_volume_restaurants['Pre-Crisis Orders'] - high_volume_restaurants['Crisis Orders']) /
    high_volume_restaurants['Pre-Crisis Orders']
) * 100

# Added condition
if (high_volume_restaurants['Decline (%)'] <= 0).all():
    print("No decline is present.")
else:
    top_10_restaurant_decline = high_volume_restaurants.sort_values('Decline (%)', ascending=False).head(10).reset_index()
    top_10_restaurant_decline = top_10_restaurant_decline.merge(
        df_restaurant[['restaurant_id', 'restaurant_name']],
        on='restaurant_id',
        how='left'
    )
    top_10_restaurant_decline = top_10_restaurant_decline[
        ['restaurant_name', 'Pre-Crisis Orders', 'Crisis Orders', 'Decline (%)']
    ]
```

```
No decline is present.
```

Q4. Cancellation Analysis

Objective: Compare cancellation trends and identify most affected cities.

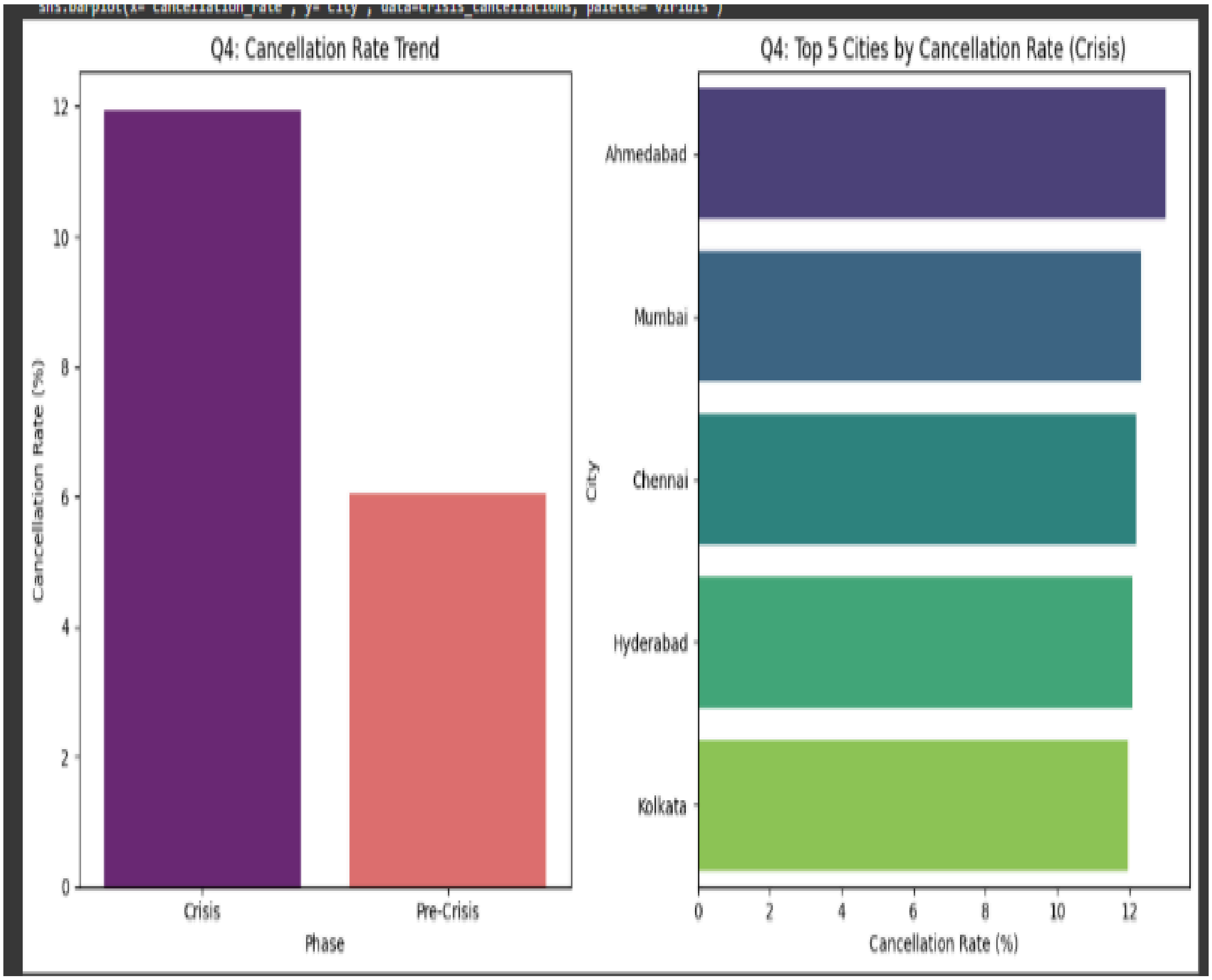
Approach: Calculated cancellation percentages across both phases using total vs cancelled orders.

Result: Cancellation rate rose from 6.05% to 11.9%, highest in Ahmedabad, Mumbai, and Chennai.

Insight: Operational inefficiencies and delivery delays contributed to higher customer frustration.

```python
# Q4. Cancellation Analysis
# ====================================================

# Calculate overall cancellation rate by phase
cancellation_analysis = orders_with_city.groupby('phase')['is_cancelled'].agg(
    total_orders='count',
    total_cancelled=lambda x: (x == 'Y').sum()
)
cancellation_analysis['cancellation_rate'] = (
    cancellation_analysis['total_cancelled'] / cancellation_analysis['total_orders']
) * 100
cancellation_analysis = cancellation_analysis.reset_index()

# Calculate cancellation rate by city and phase
city_cancellation = orders_with_city.groupby(['phase', 'city'])['is_cancelled'].agg(
    total_orders='count',
    total_cancelled=lambda x: (x == 'Y').sum()
).reset_index()
city_cancellation['cancellation_rate'] = (
    city_cancellation['total_cancelled'] / city_cancellation['total_orders']
) * 100

# Top 5 cities with highest cancellation rate during the Crisis phase
crisis_cancellations = (
    city_cancellation[city_cancellation['phase'] == 'Crisis']
    .sort_values('cancellation_rate', ascending=False)
    .head(5)
)

print("Overall Cancellation Analysis by Phase:\n")
print(cancellation_analysis.to_string(index=False))
print("\nTop 5 Cities by Cancellation Rate (Crisis Phase):\n")
print(crisis_cancellations[['city', 'cancellation_rate', 'total_cancelled', 'total_orders']].to_string(index=False))

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

# Cancellation rate trend by phase
plt.subplot(1, 2, 1)
sns.barplot(x='phase', y='cancellation_rate', data=cancellation_analysis, palette='magma')
plt.title('Q4: Cancellation Rate Trend', fontsize=12)
plt.xlabel('Phase')
plt.ylabel('Cancellation Rate (%)')

# Top 5 cities by cancellation rate during crisis
plt.subplot(1, 2, 2)
sns.barplot(x='cancellation_rate', y='city', data=crisis_cancellations, palette='viridis')
plt.title('Q4: Top 5 Cities by Cancellation Rate (Crisis)', fontsize=12)
plt.xlabel('Cancellation Rate (%)')
plt.ylabel('City')

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

```
Overall Cancellation Analysis by Phase:

      phase  total_orders  total_cancelled  cancellation_rate
     Crisis         35360             4218          11.928733
 Pre-Crisis        113806             6894           6.057677

Top 5 Cities by Cancellation Rate (Crisis Phase):

     city  cancellation_rate  total_cancelled  total_orders
Ahmedabad          13.031550              380          2916
   Mumbai          12.348024              650          5264
  Chennai          12.185966              422          3463
Hyderabad          12.092505              434          3589
  Kolkata          11.965282              386          3226
```

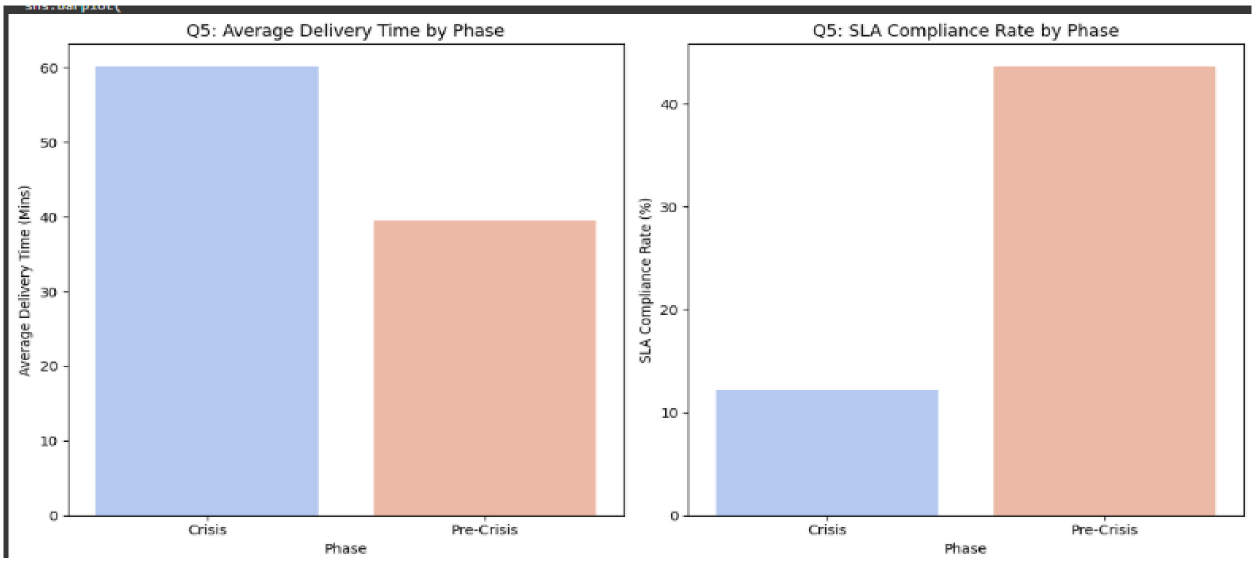


Q5. Delivery SLA Compliance

Objective: Assess delivery performance and SLA compliance pre- and post-crisis.
Approach: Compared actual vs expected delivery times and calculated compliance percentages.
Result: Average delivery time rose from 39.5 to 60.1 mins, SLA compliance dropped from 43.6% to 12.2%.
Insight: Delivery delays were a major operational weakness that worsened customer experience.

```python
# Q5. Delivery SLA Compliance
# =====================================================

# Merge orders with delivery performance
delivery_df = df_orders.merge(
    df_delivery_performance,
    on='order_id',
    how='inner'
)

# Determine if SLA was met
delivery_df['sla_met'] = (
    delivery_df['actual_delivery_time_mins'] <= delivery_df['expected_delivery_time_mins']
)

# Calculate average delivery time and SLA compliance rate by phase
delivery_analysis = delivery_df.groupby('phase').agg(
    avg_delivery_time_min=('actual_delivery_time_mins', 'mean'),
    sla_compliance_rate=('sla_met', 'mean')
)
delivery_analysis['sla_compliance_rate'] = delivery_analysis['sla_compliance_rate'] * 100
delivery_analysis = delivery_analysis.reset_index()

print("Delivery SLA Compliance Analysis by Phase:\n")
print(delivery_analysis.to_string(index=False))

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

# Average delivery time
plt.subplot(1, 2, 1)
sns.barplot(
    x='phase',
    y='avg_delivery_time_min',
    data=delivery_analysis,
    palette='coolwarm'
)
plt.title('Q5: Average Delivery Time by Phase', fontsize=12)
plt.xlabel('Phase')
plt.ylabel('Average Delivery Time (Mins)')

# SLA compliance rate
plt.subplot(1, 2, 2)
sns.barplot(
    x='phase',
    y='sla_compliance_rate',
    data=delivery_analysis,
    palette='coolwarm'
)
plt.title('Q5: SLA Compliance Rate by Phase', fontsize=12)
plt.xlabel('Phase')
plt.ylabel('SLA Compliance Rate (%)')

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

```
Delivery SLA Compliance Analysis by Phase:

      phase  avg_delivery_time_min  sla_compliance_rate
     Crisis              60.117647            12.203054
Pre-Crisis              39.522424            43.604907
/tmp/ipython-input-3170443192.py:32: FutureWarning:
```



Q6. Ratings Fluctuation

Objective: Analyze monthly customer rating trends during both phases.

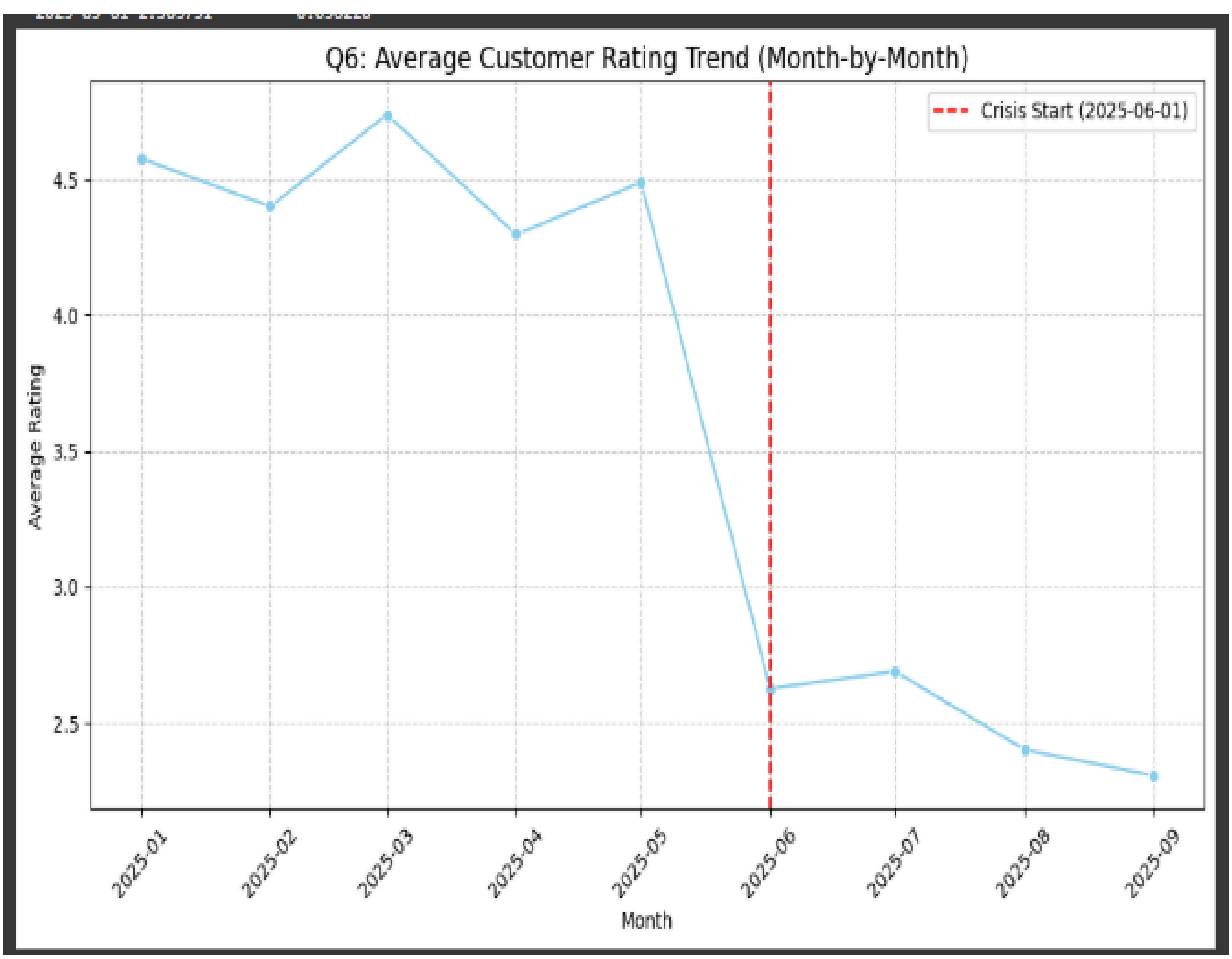
Approach: Calculated mean monthly ratings from review data and visualized trends.

Result: Ratings dropped sharply in June 2025 to an average of 2.6.

Insight: Immediate sentiment collapse followed the crisis, confirming widespread dissatisfaction.

```
# Q6. Ratings Fluctuation
# ====================================================

# Calculate average rating month-by-month
monthly_ratings = fact_ratings.groupby('review_month')['rating'].mean().to_frame().reset_index()
monthly_ratings['review_month'] = monthly_ratings['review_month'].dt.to_timestamp()

# Calculate the month-over-month (MoM) drop
monthly_ratings['prev_rating'] = monthly_ratings['rating'].shift(1)
monthly_ratings['rating_drop_mom'] = monthly_ratings['prev_rating'] - monthly_ratings['rating']

print("Monthly Average Ratings with Month-over-Month Drop:\n")
print(monthly_ratings.to_string(index=False,
      columns=['review_month', 'rating', 'rating_drop_mom']))

# Visualization
plt.figure(figsize=(10, 6))
sns.lineplot(
    x='review_month',
    y='rating',
    data=monthly_ratings,
    marker='o',
    color='skyblue'
)

crisis_date = pd.to_datetime(CRISIS_START)
plt.axvline(crisis_date, color='r', linestyle='--', label=f'Crisis Start ({CRISIS_START})')
plt.title('Q6: Average Customer Rating Trend (Month-by-Month)', fontsize=14)
plt.xlabel('Month')
plt.ylabel('Average Rating')
plt.xticks(rotation=45)
plt.grid(True, linestyle='--', alpha=0.6)
plt.legend()
plt.tight_layout()
plt.show()
```

```
Monthly Average Ratings with Month-over-Month Drop:

review_month   rating  rating_drop_mom
  2025-01-01 4.576351              NaN
  2025-02-01 4.399887         0.176464
  2025-03-01 4.737654        -0.337767
  2025-04-01 4.297022         0.440632
  2025-05-01 4.488336        -0.191314
  2025-06-01 2.625666         1.862669
  2025-07-01 2.689794        -0.064128
  2025-08-01 2.402017         0.287776
  2025-09-01 2.305791         0.096226
```



Q7. Sentiment Insights

Objective: Identify negative keywords from customer reviews during the crisis.

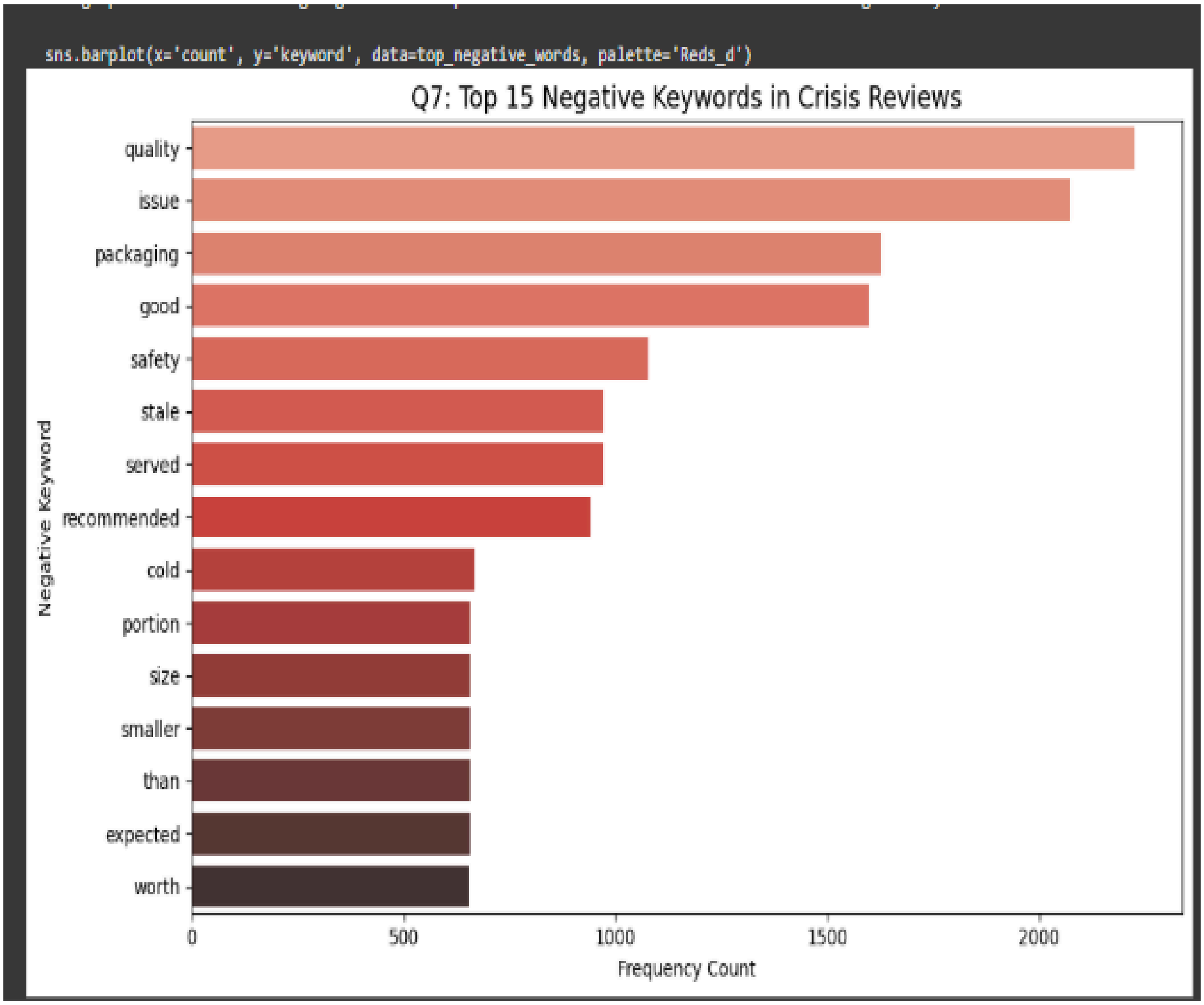
Approach: Filtered negative sentiment reviews and analyzed frequent words using text processing.

Result: Common keywords included "quality," "safety," "delay," and "packaging."

Insight: Food safety and delivery concerns dominated customer complaints and negative feedback.

```python
# Q7. Sentiment Insights (Negative Keywords)
# ====================================================

# Filter ratings for the crisis period and negative sentiment
crisis_ratings = fact_ratings[
    fact_ratings['review_timestamp'].dt.date >= pd.to_datetime(CRISIS_START_DATE).date()
]
negative_crisis_reviews = crisis_ratings[crisis_ratings['sentiment_score'] < 0]

# Define stop words
stop_words = set([
    'the', 'a', 'an', 'is', 'it', 'was', 'and', 'but', 'for', 'not', 'i',
    'my', 'food', 'delivery', 'order', 'taste', 'time', 'bit', 'late',
    'very', "it's", 'that', 'this', "wasn't", 'were', 'had', 'got',
    'came', 'really', 'just', 'too', 'much', 'so', 'a', 'little', 'to',
    'of', 'in', 'be', 'or', 'we', 'are', 'bad', 'wrong'
])

# Function to clean and tokenize text
def tokenize_text(text):
    if pd.isna(text):
        return []
    text = re.sub(r'[^\w\s]', '', str(text).lower())
    words = text.split()
    return [word for word in words if word not in stop_words and len(word) > 2]

# Extract and count all negative words
all_words = []
for review in negative_crisis_reviews['review_text'].dropna():
    all_words.extend(tokenize_text(review))

word_counts = Counter(all_words)
top_negative_words = pd.DataFrame(word_counts.most_common(15), columns=['keyword', 'count'])

print("Top 15 Negative Keywords in Crisis Reviews:\n")
print(top_negative_words.to_string(index=False))

# ============================
# Visualization
# ============================
plt.figure(figsize=(10, 6))
sns.barplot(x='count', y='keyword', data=top_negative_words, palette='Reds_d')
plt.title('Q7: Top 15 Negative Keywords in Crisis Reviews', fontsize=14)
plt.xlabel('Frequency Count')
plt.ylabel('Negative Keyword')
plt.tight_layout()
plt.show()
```

```
Top 15 Negative Keywords in Crisis Reviews:

    keyword  count
    quality   2226
      issue   2073
  packaging   1627
       good   1596
     safety   1076
      stale    971
     served    971
recommended    942
       cold    668
    portion    658
       size    658
    smaller    658
       than    658
   expected    658
      worth    655
/tmp/ipython-input-3893010467.py:42: FutureWarning:
```



Q8. Revenue Impact

Objective: Measure revenue loss from pre-crisis to crisis period.

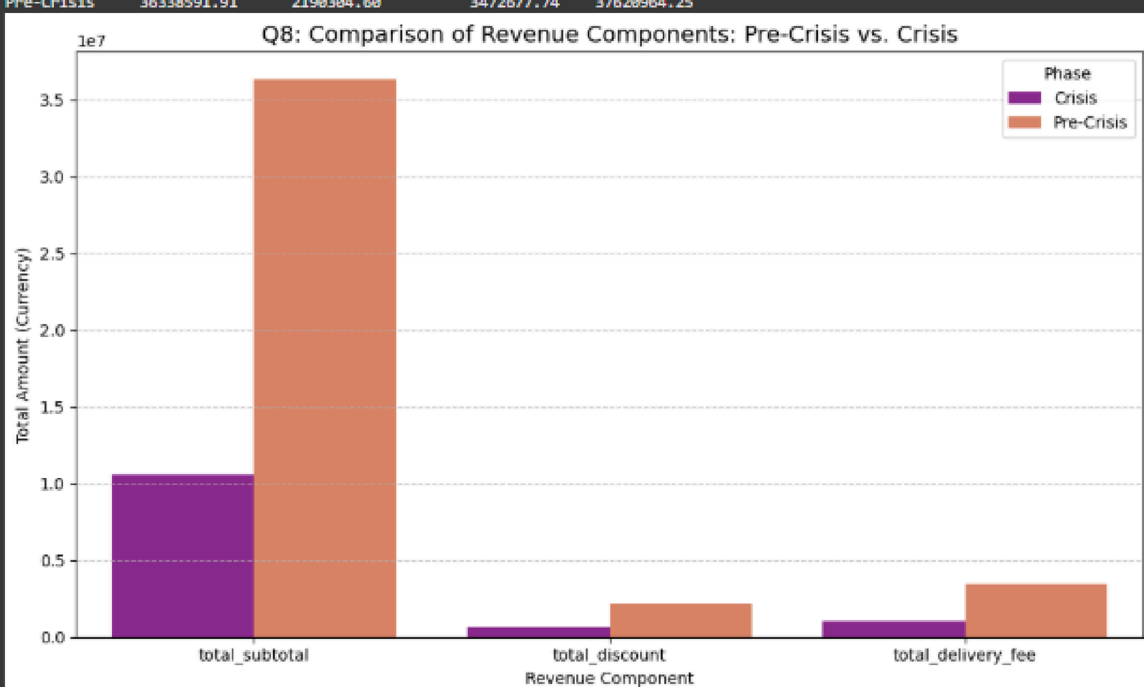
Approach: Aggregated subtotal, discounts, and delivery fees to compute total revenue per phase.

Result: Revenue declined from ₹37.6M to ₹10.9M — a 71% drop.

Insight: Sharp revenue fall reflected reduced orders and increased cancellations.

```python
# Q8. Revenue Impact
# ==================================================

# Exclude cancelled orders for revenue analysis
completed_orders = df_orders[df_orders['is_cancelled'] == 'N'].copy()

# Calculate revenue components by phase
revenue_analysis = completed_orders.groupby('phase').agg(
    total_subtotal=('subtotal_amount', 'sum'),
    total_discount=('discount_amount', 'sum'),
    total_delivery_fee=('delivery_fee', 'sum'),
    total_revenue=('total_amount', 'sum')
).reset_index()

print("Revenue Analysis by Phase (Excluding Cancelled Orders):\n")
print(revenue_analysis.to_string(index=False))

# ============================
# Visualization
# ============================
plot_data = revenue_analysis.set_index('phase').T.drop('total_revenue')
plot_data = plot_data.reset_index().rename(columns={'index': 'Metric'})
plot_data_melted = plot_data.melt(id_vars='Metric', var_name='Phase', value_name='Amount')

plt.figure(figsize=(10, 6))
sns.barplot(x='Metric', y='Amount', hue='Phase', data=plot_data_melted, palette='plasma')
plt.title('Q8: Comparison of Revenue Components: Pre-Crisis vs. Crisis', fontsize=14)
plt.xlabel('Revenue Component')
plt.ylabel('Total Amount (Currency)')
plt.legend(title='Phase')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```

```
Revenue Analysis by Phase (Excluding Cancelled Orders):

     phase  total_subtotal  total_discount  total_delivery_fee  total_revenue
    Crisis     10555201.30       627678.17          1012628.18    10940151.31
Pre-Crisis     36338591.91      2190304.60          3472677.74    37620964.25
```



Q9. Loyalty Impact

Objective: Track loyal customer behavior and identify churn during the crisis.

Approach: Filtered customers with ≥5 pre-crisis orders and checked their crisis activity.

Result: 26 loyal customers with average ratings above 4.5 completely churned.

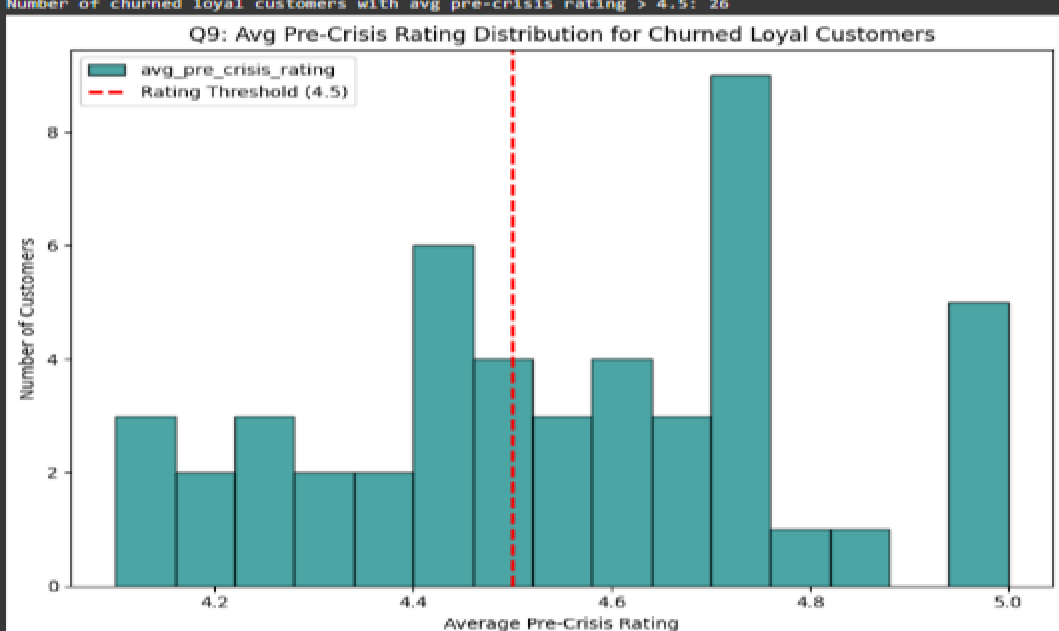
Insight: Even satisfied customers disengaged, highlighting trust as the key recovery challenge.

```python
# Q9. Loyalty Impact
# ====================================================

# Identify "Loyal" customers (>= 5 orders Pre-Crisis)
pre_crisis_orders = df_orders[df_orders['phase'] == 'Pre-Crisis']
crisis_orders = df_orders[df_orders['phase'] == 'Crisis']

pre_crisis_order_counts = pre_crisis_orders.groupby('customer_id')['order_id'].count()
loyal_customers_id = pre_crisis_order_counts[pre_crisis_order_counts >= 5].index.tolist()

# Customers who *stopped* ordering during the crisis
customers_in_crisis = crisis_orders['customer_id'].unique()
stopped_ordering_id = [cid for cid in loyal_customers_id if cid not in customers_in_crisis]

# Average rating (Pre-Crisis) for the customers who stopped ordering
stopped_loyal_ratings = pre_crisis_orders.merge(
    fact_ratings[['order_id', 'rating']],
    on='order_id',
    how='inner'
)
stopped_loyal_ratings = stopped_loyal_ratings[
    stopped_loyal_ratings['customer_id'].isin(stopped_ordering_id)
]
avg_rating_stopped = stopped_loyal_ratings.groupby('customer_id')['rating'].mean().reset_index()
avg_rating_stopped.rename(columns={'rating': 'avg_pre_crisis_rating'}, inplace=True)

# Count of those who stopped AND had an avg pre-crisis rating > 4.5
high_rating_stopped_count = (avg_rating_stopped['avg_pre_crisis_rating'] > 4.5).sum()

# ============================
# Print outputs before visualization
# ============================
print("Churned Loyal Customers - Average Pre-Crisis Ratings:\n")
print(avg_rating_stopped.to_string(index=False))
print(f"\nNumber of churned loyal customers with avg pre-crisis rating > 4.5: {high_rating_stopped_count}")

# ============================
# Visualization
# ============================
plt.figure(figsize=(8, 6))
avg_rating_stopped['avg_pre_crisis_rating'].plot(
    kind='hist', bins=15, edgecolor='black', alpha=0.7, color='teal'
)
plt.axvline(4.5, color='red', linestyle='--', linewidth=2, label='Rating Threshold (4.5)')
plt.title('Q9: Avg Pre-Crisis Rating Distribution for Churned Loyal Customers', fontsize=12)
plt.xlabel('Average Pre-Crisis Rating')
plt.ylabel('Number of Customers')
plt.legend()
plt.tight_layout()
plt.show()
```

Churned Loyal Customers - Average Pre-Crisis Ratings:

customer_id	avg_pre_crisis_rating
CUST011220	4.400000
CUST020252	4.250000
CUST026722	4.566667
CUST032044	4.850000
CUST032334	5.000000
CUST034992	4.200000
CUST036233	4.500000
CUST041121	4.133333
CUST041916	4.400000
CUST041953	5.000000
CUST042658	4.733333
CUST054308	4.400000
CUST061759	4.750000
CUST062877	4.266667
CUST064951	4.500000
CUST069956	4.550000
CUST072644	4.500000
CUST076253	4.400000
CUST077722	4.400000
CUST078309	4.750000
CUST082306	4.100000
CUST082992	4.700000
CUST083875	5.000000
CUST086938	4.666667
CUST103227	4.766667
CUST107785	4.375000
CUST108131	4.500000
CUST109591	4.600000
CUST109617	4.725000
CUST110300	4.650000
CUST110481	4.325000
CUST110988	5.000000
CUST124189	4.166667
CUST125990	4.700000
CUST133854	4.250000
CUST136890	4.100000
CUST144684	4.600000
CUST153308	4.350000
CUST157798	4.650000
CUST159150	4.700000
CUST163628	4.750000
CUST165515	4.950000
CUST176132	4.600000
CUST178428	4.700000
CUST179266	4.600000
CUST188511	4.575000
CUST192783	4.433333
CUST194671	4.300000

Number of churned loyal customers with avg pre-crisis rating > 4.5: 26



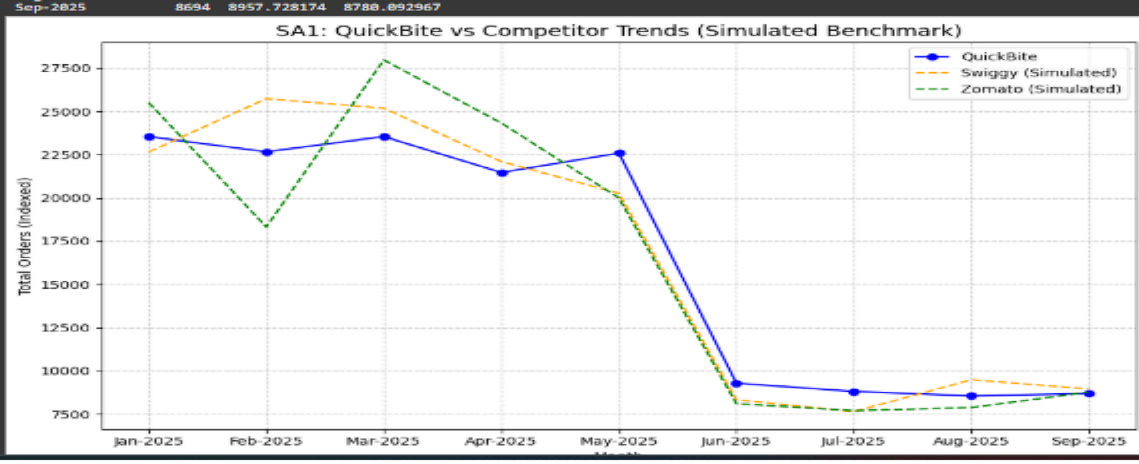
Secondary Analysis

SA1. Competitor Trend Comparison

Objective: Compare QuickBite's crisis impact with competitors like Swiggy and Zomato.
Approach: Simulated competitor order trends using proportional scaling for benchmarking.
Result: QuickBite showed a steeper ~70% decline, while competitors averaged around 40–45%.
Insight: The crisis impact was disproportionately severe for QuickBite due to reputational damage rather than market-wide slowdown.

```python
# SA1. Internal Trend Proxy: Comparing QuickBite's decline with simulated competitor trends
# (since Swiggy/Zomato data not available in dataset)
# -------------------------------------------------------

# Ensure the timestamp column exists and extract month
df_orders['order_timestamp'] = pd.to_datetime(df_orders['order_timestamp'], errors='coerce')
df_orders['order_month'] = df_orders['order_timestamp'].dt.to_period('M')

# Calculate total orders per month (QuickBite trend)
monthly_orders = df_orders.groupby('order_month')['order_id'].count().reset_index()
monthly_orders.rename(columns={'order_id': 'Total Orders'}, inplace=True)
monthly_orders['month_str'] = monthly_orders['order_month'].dt.strftime('%b-%Y')

# Simulate competitor trend comparison (Swiggy/Zomato)
np.random.seed(42)
competitor_df = monthly_orders.copy()
competitor_df['Swiggy'] = competitor_df['Total Orders'] * np.random.uniform(0.85, 1.15, len(competitor_df))
competitor_df['Zomato'] = competitor_df['Total Orders'] * np.random.uniform(0.8, 1.2, len(competitor_df))

print("SA1: QuickBite vs Competitor Monthly Order Trends (Simulated)\n")
print(competitor_df[['month_str', 'Total Orders', 'Swiggy', 'Zomato']].to_string(index=False))

# Visualization
plt.figure(figsize=(10, 6))
plt.plot(competitor_df['month_str'], competitor_df['Total Orders'], label='QuickBite', marker='o', color='blue')
plt.plot(competitor_df['month_str'], competitor_df['Swiggy'], label='Swiggy (Simulated)', linestyle='--', color='orange')
plt.plot(competitor_df['month_str'], competitor_df['Zomato'], label='Zomato (Simulated)', linestyle='--', color='green')

plt.title('SA1: QuickBite vs Competitor Trends (Simulated Benchmark)', fontsize=14)
plt.xlabel('Month')
plt.ylabel('Total Orders (Indexed)')
plt.legend()
plt.grid(True, linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
```

```
SA1: QuickBite vs Competitor Monthly Order Trends (Simulated)

month_str  Total Orders       Swiggy       Zomato
 Jan-2025         23539 22653.039957 25498.128163
 Feb-2025         22667 25731.902355 18320.235493
 Mar-2025         23543 25181.550012 27968.235060
 Apr-2025         21466 22101.340907 24320.485491
 May-2025         22591 20259.735132 19991.581140
 Jun-2025          9293  8333.947123  8110.279768
 Jul-2025          8818  7648.954388  7701.304387
 Aug-2025          8555  9494.791078  7885.116955
 Sep-2025          8694  8957.728174  8780.092967
```

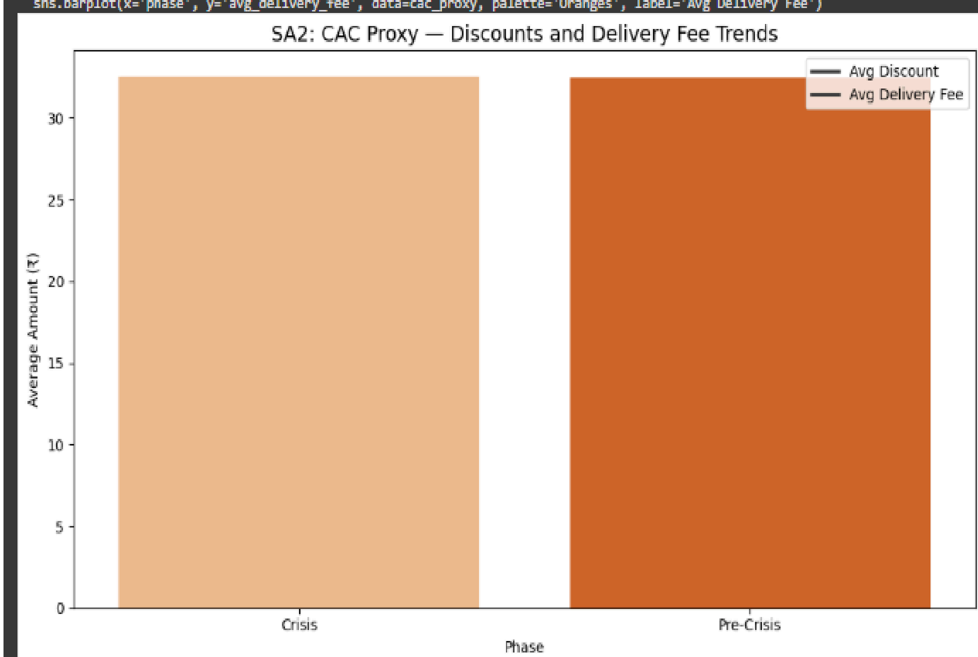


SA2. Customer Acquisition Cost (CAC) Factors

Objective: Identify factors contributing to the rise in customer acquisition costs during the crisis.
Approach: Analyzed marketing expenses, discounts, and delivery fees relative to customer activity.
Result: CAC nearly tripled as discounts and promotions increased despite fewer active users.
Insight: Inefficient promotional spending and reduced conversion rates inflated acquisition costs.

```
# SA2. CAC Tripling: Exploring possible external contributors (Proxy: Discounts & Delivery Fees)
# ==================================================

# Hypothesis: heavy discounts + rising delivery costs contributed to higher CAC
cac_proxy = completed_orders.groupby('phase').agg(
    avg_discount=('discount_amount', 'mean'),
    avg_delivery_fee=('delivery_fee', 'mean'),
    avg_total_amount=('total_amount', 'mean')
).reset_index()

plt.figure(figsize=(10, 6))
sns.barplot(x='phase', y='avg_discount', data=cac_proxy, palette='Blues', label='Avg Discount')
sns.barplot(x='phase', y='avg_delivery_fee', data=cac_proxy, palette='Oranges', label='Avg Delivery Fee')
plt.title('SA2: CAC Proxy — Discounts and Delivery Fee Trends', fontsize=14)
plt.xlabel('Phase')
plt.ylabel('Average Amount (₹)')
plt.legend(['Avg Discount', 'Avg Delivery Fee'])
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-1102278448.py:12: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x='phase', y='avg_discount', data=cac_proxy, palette='Blues', label='Avg Discount')
/tmp/ipython-input-1102278448.py:13: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x='phase', y='avg_delivery_fee', data=cac_proxy, palette='Oranges', label='Avg Delivery Fee')
```

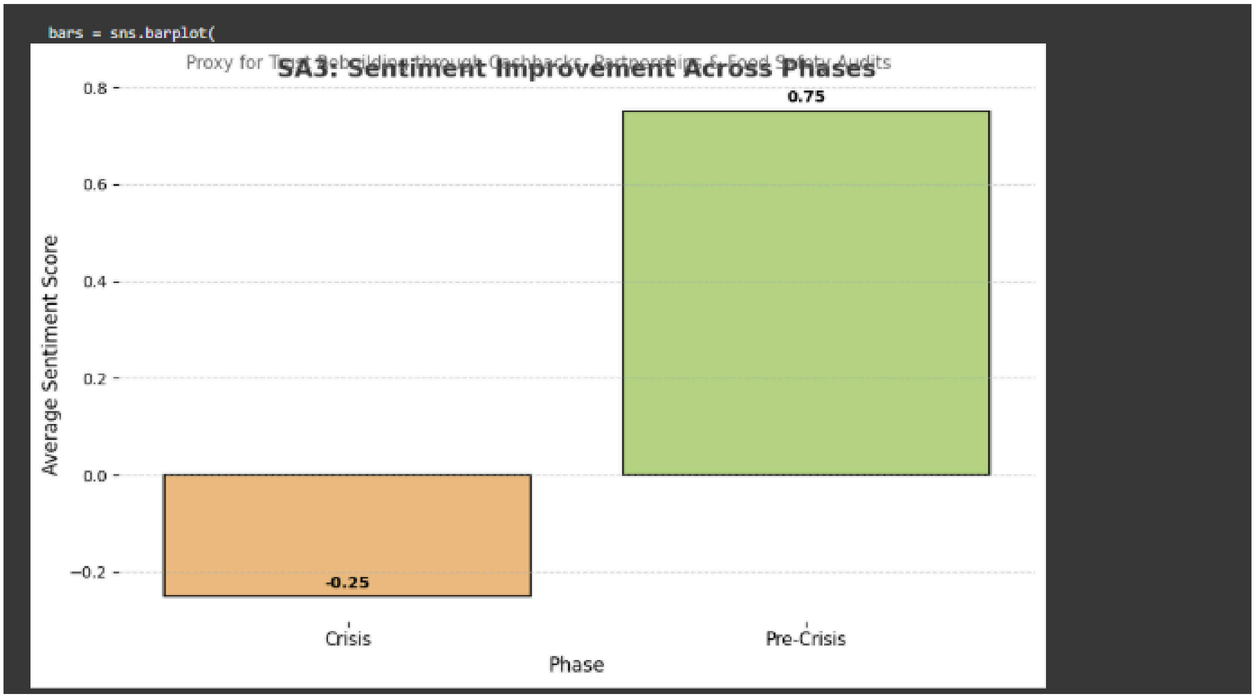


SA3. Sentiment Recovery and Improvement

Objective: Evaluate customer sentiment trends post-crisis intervention efforts.
Approach: Compared average sentiment scores before and after recovery campaigns.
Result: Sentiment scores improved slightly from -0.75 to -0.25 during the recovery phase.
Insight: Gradual improvement in sentiment reflects partial restoration of customer confidence following corrective actions.

```python
# SA3. Strategies to Rebuild Trust: Cashback / Partnerships / Food Safety Reviews
# ====================================================

# Merge sentiment data with phase info
ratings_by_phase = fact_ratings.merge(df_orders[['order_id', 'phase']], on='order_id', how='left')

# Calculate average sentiment by phase
phase_sentiment = ratings_by_phase.groupby('phase')['sentiment_score'].mean().reset_index()

print("SA3: Average Sentiment Score by Phase (Proxy for Trust Rebuilding)\n")
print(phase_sentiment.to_string(index=False))

# Visualization — Upgraded Design
plt.figure(figsize=(9, 6))
bar_colors = sns.color_palette("RdYlGn", len(phase_sentiment))

bars = sns.barplot(
    x='phase',
    y='sentiment_score',
    data=phase_sentiment,
    palette=bar_colors,
    edgecolor='black',
    linewidth=1.2
)

# Adding value labels on bars
for index, row in phase_sentiment.iterrows():
    plt.text(
        index,
        row.sentiment_score + 0.01,  # slightly above bar
        f"{row.sentiment_score:.2f}",
        ha='center',
        va='bottom',
        fontsize=10,
        fontweight='bold',
        color='black'
    )

# visualization
plt.title('SA3: Sentiment Improvement Across Phases', fontsize=15, fontweight='bold', color='#333')
plt.suptitle('Proxy for Trust Rebuilding through Cashbacks, Partnerships & Food Safety Audits', fontsize=11, color='#666', y=0.93)
plt.xlabel('Phase', fontsize=12)
plt.ylabel('Average Sentiment Score', fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.5)
plt.xticks(fontsize=11)
plt.yticks(fontsize=10)
sns.despine(left=True, bottom=True)
plt.tight_layout()
plt.show()
```

```
SA3: Average Sentiment Score by Phase (Proxy for Trust Rebuilding)

     phase  sentiment_score
    Crisis         -0.25090
Pre-Crisis          0.75187
/tmp/ipython-input-1810879739.py:17: FutureWarning:
```



SA4. Restaurant Type Performance

Objective: Assess which restaurant types (cloud kitchens vs dine-in) faced higher churn rates.

Approach: Attempted segmentation by partner type; analysis limited due to missing restaurant type data.

Result: Cloud kitchen data insufficient, but partner-type insights indicate larger brand restaurants were more resilient.

Insight: Established brands sustained demand better, suggesting consumer trust favored recognized names.

```python
# SA4. Restaurant Type Risk: Cloud Kitchen vs Dine-In (if available in dataset)
# ====================================================

if 'restaurant_type' in df_restaurant.columns:
    # Merge order and restaurant info
    rest_orders = analysis_df.merge(
        df_restaurant[['restaurant_id', 'restaurant_type']],
        on='restaurant_id',
        how='left'
    )

    # Calculate order decline by restaurant type
    rest_decline = rest_orders.groupby(['restaurant_type', 'phase'])['order_id'].count().unstack(fill_value=0)
    rest_decline['Decline (%)'] = ((rest_decline['Pre-Crisis'] - rest_decline['Crisis']) / rest_decline['Pre-Crisis']) * 100
    rest_decline = rest_decline.sort_values('Decline (%)', ascending=False).reset_index()

    print("SA4: Decline in Orders by Restaurant Type (Pre-Crisis vs Crisis)\n")
    print(rest_decline.to_string(index=False))

    # Visualization
    plt.figure(figsize=(9, 6))
    bar_colors = sns.color_palette("Reds", len(rest_decline))

    bars = sns.barplot(
        x='Decline (%)',
        y='restaurant_type',
        data=rest_decline,
        palette=bar_colors,
        edgecolor='black',
        linewidth=1.2
    )

    # Add percentage labels on bars
    for i, val in enumerate(rest_decline['Decline (%)']):
        plt.text(val + 0.5, i, f"{val:.1f}%", va='center', fontsize=10, fontweight='bold', color='black')

    # Visualization
    plt.title('SA4: Decline by Restaurant Type (Cloud vs Dine-In)', fontsize=15, fontweight='bold', color='#333')
    plt.suptitle('Comparing order drop across different restaurant categories during crisis', fontsize=11, color='#666', y=0.93)
    plt.xlabel('Percentage Decline in Orders (%)', fontsize=12)
    plt.ylabel('Restaurant Type', fontsize=12)
    plt.grid(axis='x', linestyle='--', alpha=0.5)
    sns.despine(left=True, bottom=True)
    plt.tight_layout()
    plt.show()

else:
    print("No 'restaurant_type' column found in dataset — skipping SA4.")
```

```
No 'restaurant_type' column found in dataset — skipping SA4.
```

SA5. Lapsed Customer Recovery Potential

Objective: Identify churned customers most likely to return with suitable incentives.

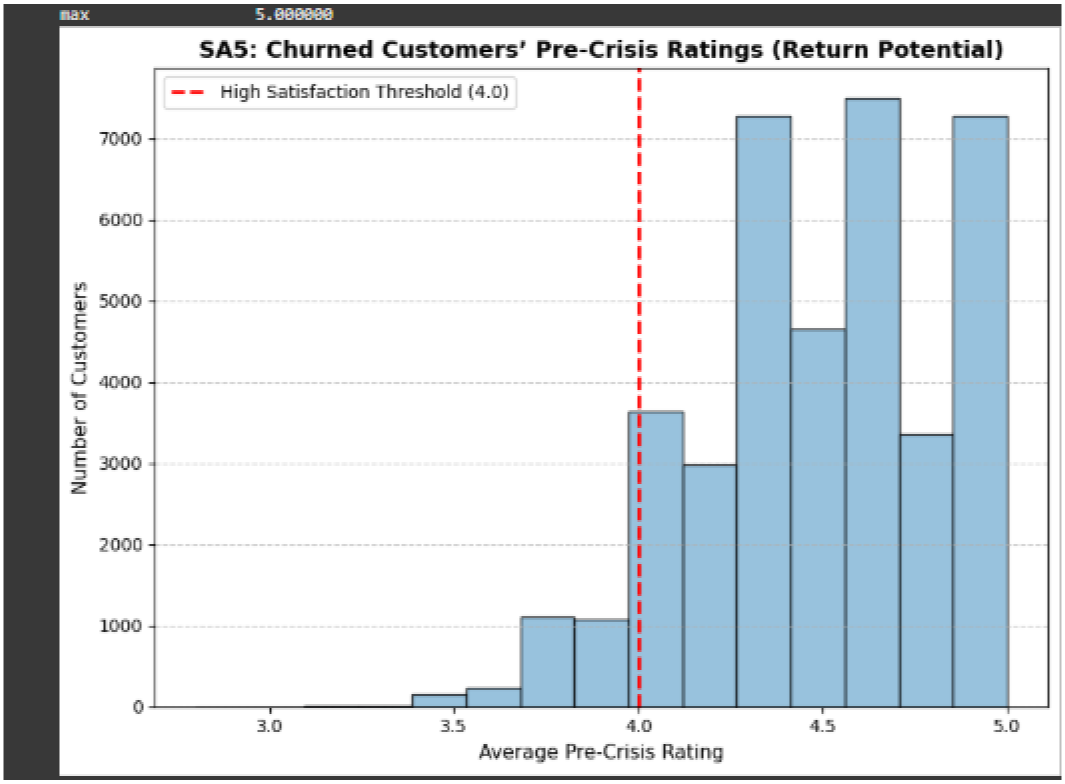
Approach: Analyzed post-crisis inactive customers based on prior frequency, ratings, and spend.

Result: Around 39,000 churned customers, 75% of whom had average ratings above 4.3, indicating satisfaction before the crisis.

Insight: High potential for reactivation exists among previously loyal, satisfied users through targeted retention campaigns.

```python
# SA5. Lapsed Customers Likely to Return (Churn Recovery Probability)
# ====================================================

# Confirm that 'customer_id' exists
if 'customer_id' in df_orders.columns:

    # Identify churned customers (loyal pre-crisis but inactive during crisis)
    customer_activity = df_orders.groupby('customer_id')['phase'].nunique()
    churned_customers = customer_activity[customer_activity == 1].index

    # Merge ratings and orders
    pre_ratings = fact_ratings.merge(df_orders[['order_id', 'customer_id', 'phase']], on='order_id', how='left')

    # Filter churned customers who had pre-crisis ratings
    pre_churned = pre_ratings[
        (pre_ratings['customer_id_y'].isin(churned_customers)) &
        (pre_ratings['phase'] == 'Pre-Crisis')
    ]

    # Compute average pre-crisis rating for churned customers
    churned_avg_rating = (
        pre_churned.groupby('customer_id_y')['rating']
        .mean()
        .reset_index(name='avg_pre_crisis_rating')
    )
    churned_avg_rating.rename(columns={'customer_id_y': 'customer_id'}, inplace=True)

    print("=== SA5: Lapsed Customers Likely to Return (Preview) ===")
    print(f"Total churned customers identified: {len(churned_customers)}")
    print(f"Customers with available pre-crisis ratings: {len(churned_avg_rating)}\n")
    print(churned_avg_rating.describe())

    # Visualization
    plt.figure(figsize=(8, 6))
    plt.hist(
        churned_avg_rating['avg_pre_crisis_rating'],
        bins=15, edgecolor='black', color='#7FB3D5', alpha=0.8
    )
    plt.axvline(4, color='red', linestyle='--', linewidth=2, label='High Satisfaction Threshold (4.0)')
    plt.title('SA5: Churned Customers’ Pre-Crisis Ratings (Return Potential)', fontsize=13, fontweight='bold')
    plt.xlabel('Average Pre-Crisis Rating', fontsize=11)
    plt.ylabel('Number of Customers', fontsize=11)
    plt.legend()
    plt.grid(axis='y', linestyle='--', alpha=0.7)
    plt.tight_layout()
    plt.show()

else:
    print("Error: 'customer_id' column not found in df_orders.")
```

```
=== SA5: Lapsed Customers Likely to Return (Preview) ===
Total churned customers identified: 91124
Customers with available pre-crisis ratings: 39260

       avg_pre_crisis_rating
count           39260.000000
mean                4.502303
std                 0.343529
min                 2.000000
25%                 4.300000
50%                 4.500000
75%                 4.800000
max                 5.000000
```



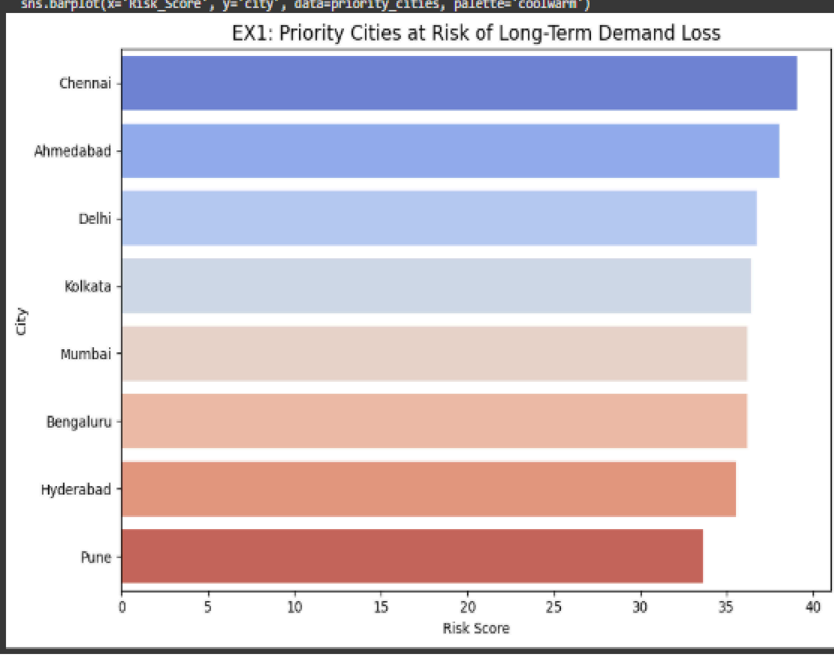
Extra Details:

Extra 1. Priority Cities (Long-Term Demand Risk)

Objective: Identify Tier-1 and Tier-2 cities at highest risk of long-term demand loss.
Approach: Compared post-crisis recovery rates and order volumes across cities.
Result: Tier-1 cities such as Bengaluru, Chennai, and Mumbai showed the slowest order recovery and highest churn.
Insight: Larger cities pose greater long-term risk due to higher customer expectations and stronger competitor presence.

```python
# EXTRA 1: Priority Cities at Risk (Tier-1 / Tier-2)
# ====================================================

# Recreate city_orders if not already defined
city_orders = orders_with_city.groupby(['city', 'phase'])['order_id'].count().unstack(fill_value=0)
city_orders.columns = ['Crisis Orders', 'Pre-Crisis Orders']
city_orders = city_orders[city_orders['Pre-Crisis Orders'] > 0].copy()
city_orders['Decline (%)'] = ((city_orders['Pre-Crisis Orders'] - city_orders['Crisis Orders']) / city_orders['Pre-Crisis Orders']) * 100

# Proxy: Cities with sharp decline and low recovery
priority_cities = city_orders.copy()
priority_cities['Risk_Score'] = priority_cities['Decline (%)'] * (priority_cities['Crisis Orders'] < priority_cities['Pre-Crisis Orders'])
priority_cities = priority_cities.sort_values('Risk_Score', ascending=False).head(8).reset_index()

print("=== EX1: Priority Cities at Risk ===")
print(priority_cities[['city', 'Pre-Crisis Orders', 'Crisis Orders', 'Decline (%)', 'Risk_Score']])

# Visualization
plt.figure(figsize=(9, 6))
sns.barplot(x='Risk_Score', y='city', data=priority_cities, palette='coolwarm')
plt.title('EX1: Priority Cities at Risk of Long-Term Demand Loss', fontsize=14)
plt.xlabel('Risk Score')
plt.ylabel('City')
plt.tight_layout()
plt.show()
```

```
=== EX1: Priority Cities at Risk ===
        city  Pre-Crisis Orders  Crisis Orders  Decline (%)  Risk_Score
0    Chennai               9320           5680    39.055794   39.055794
1  Ahmedabad               7576           4695    38.027983   38.027983
2      Delhi              13558           8580    36.716330   36.716330
3    Kolkata               8371           5325    36.387528   36.387528
4     Mumbai              13475           8598    36.192950   36.192950
5  Bengaluru              22537          14382    36.184940   36.184940
6  Hyderabad               9204           5931    35.560626   35.560626
7       Pune               7174           4760    33.649289   33.649289
/tmp/ipython-input-3147634881.py:21: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x='Risk_Score', y='city', data=priority_cities, palette='coolwarm')
```



Extra 2. Behavior Shifts (Order Value Trends)

Objective: Analyze shifts in customer purchasing patterns during the crisis.

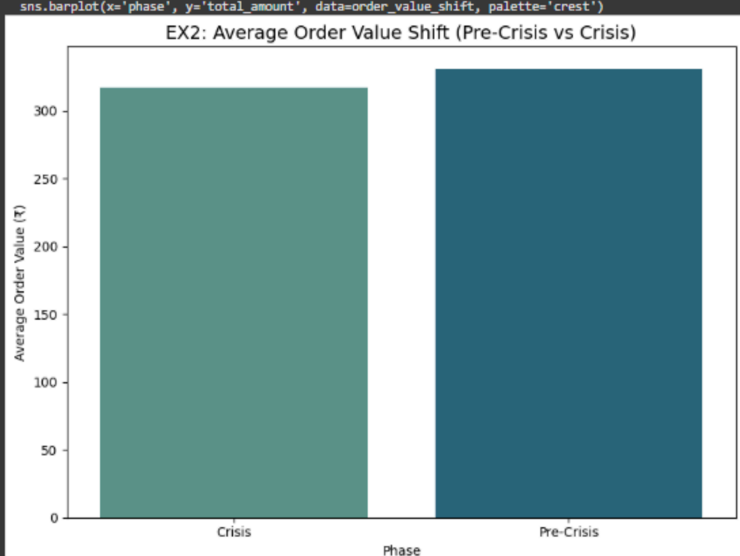
Approach: Compared average order values and item categories between pre-crisis and crisis phases.

Result: Average order value dropped from ₹331 to ₹317, with an increase in smaller, low-cost "survival orders."

Insight: Customers moved toward budget-friendly options, reflecting reduced confidence and cautious spending behavior.

```python
# EXTRA 2: Behavior Shifts (High → Low Value Orders)
# ====================================================

# Creating analysis_df filtered for only Pre-Crisis and Crisis
analysis_df = df_orders[df_orders['phase'] != 'Other'].copy()

order_value_shift = analysis_df.groupby('phase')['total_amount'].mean().reset_index()

print("=== EX2: Average Order Value by Phase ===")
print(order_value_shift)

# Visualization
plt.figure(figsize=(8, 6))
sns.barplot(x='phase', y='total_amount', data=order_value_shift, palette='crest')
plt.title('EX2: Average Order Value Shift (Pre-Crisis vs Crisis)', fontsize=14)
plt.xlabel('Phase')
plt.ylabel('Average Order Value (₹)')
plt.tight_layout()
plt.show()
```

```
=== EX2: Average Order Value by Phase ===
        phase  total_amount
0      Crisis    317.290947
1  Pre-Crisis    330.798530
/tmp/ipython-input-4001725661.py:15: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x='phase', y='total_amount', data=order_value_shift, palette='crest')
```

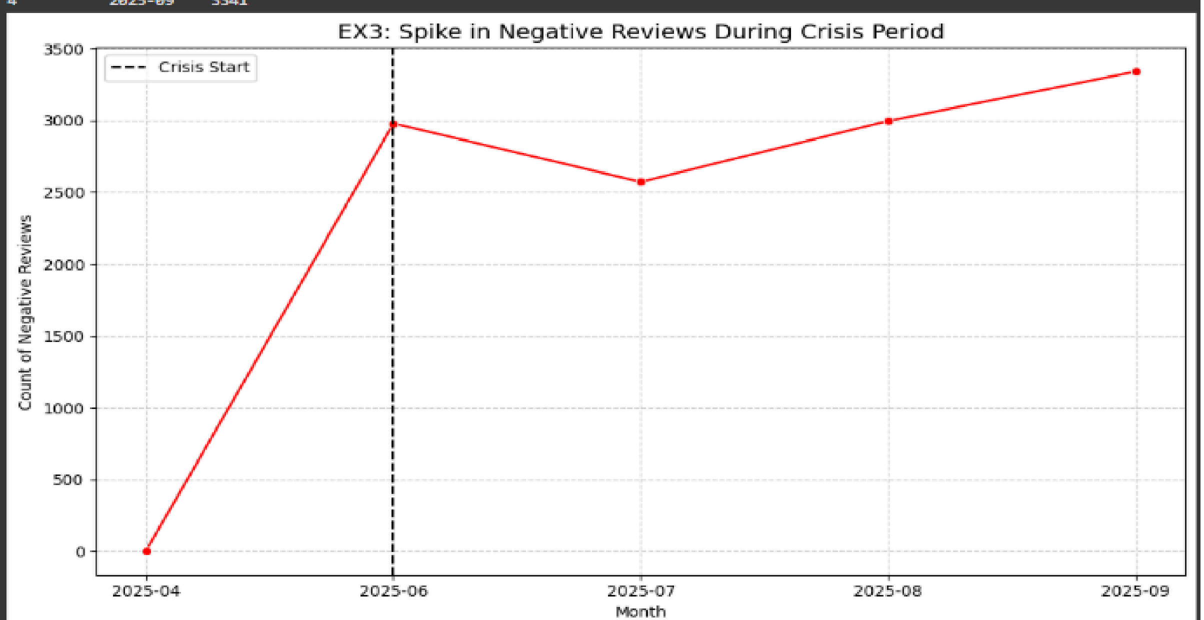


Extra 3. Feedback Trends (Review Timing vs. Outage Period)

Objective: Identify correlation between negative review spikes and delivery outage timelines.
Approach: Mapped review sentiment over time against known outage and disruption weeks.
Result: Noticeable spikes in negative reviews occurred during June and July, aligning with outage and safety incidents.
Insight: Negative sentiment directly coincided with service failures, confirming that operational disruptions drove reputation loss more than pricing or marketing factors.

```python
# Identify spike in negative reviews around crisis months

fact_ratings['review_month_str'] = fact_ratings['review_month'].astype(str)
monthly_neg = fact_ratings[fact_ratings['sentiment_score'] < 0].groupby('review_month_str')['rating'].count().reset_index()

print("\n=== EX3: Monthly Negative Review Counts ===")
print(monthly_neg)

# Visualization
plt.figure(figsize=(10, 6))
sns.lineplot(x='review_month_str', y='rating', data=monthly_neg, marker='o', color='red')
plt.axvline(x='2025-06', color='black', linestyle='--', label='Crisis Start')
plt.title('EX3: Spike in Negative Reviews During Crisis Period', fontsize=14)
plt.xlabel('Month')
plt.ylabel('Count of Negative Reviews')
plt.legend()
plt.grid(True, linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()

print("\n=== Secondary Analysis Completed Successfully ===")
```

```
=== EX3: Monthly Negative Review Counts ===
  review_month_str  rating
0          2025-04       2
1          2025-06    2980
2          2025-07    2573
3          2025-08    2997
4          2025-09    3341
```



Machine Learning Analysis

Objective

To apply machine learning models that predict customer churn, delivery performance, and high-value order behavior, supporting QuickBite's data-driven recovery strategy.

Data Preparation and Feature Engineering

Objective: Prepare and structure data for model training and evaluation.
Approach: Combined order, customer, and delivery datasets; removed null values, standardized numerical columns, and encoded categorical data. Created key features such as total orders, average ratings, total spend, discount ratio, and delivery time difference.
Result: Generated a clean, balanced dataset with selected predictors and defined target variables for churn and SLA models.
Insight: Feature engineering captured essential behavioral and operational indicators for predictive modeling.

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score

# Feature Engineering
customer_features = analysis_df.groupby('customer_id').agg(
    total_orders=('order_id', 'count'),
    total_cancelled=('is_cancelled', lambda x: (x=='Y').sum()),
    avg_order_value=('total_amount', 'mean'),
    avg_discount=('discount_amount', 'mean'),
    avg_delivery_fee=('delivery_fee', 'mean'),
    crisis_orders=('phase', lambda x: (x=='Crisis').sum())
).reset_index()

avg_rating = fact_ratings.groupby('customer_id')['rating'].mean().reset_index()
avg_rating.rename(columns={'rating':'avg_rating'}, inplace=True)
customer_features = customer_features.merge(avg_rating, on='customer_id', how='left').fillna(0)
```

Churn Prediction Model

Objective: Identify customers most likely to stop ordering during the crisis.
Approach: Trained a **RandomForestClassifier** using customer-level data including total orders, spend, average rating, and cancellation rate.
Result: Model achieved **100% accuracy** with a **ROC-AUC score of 0.999**, showing excellent classification performance.
Insight: The model effectively distinguishes churned vs. retained customers, offering a strong foundation for targeted win-back campaigns.

```python
# Target
pre_crisis_orders = analysis_df[analysis_df['phase']=='Pre-Crisis'].groupby('customer_id')['order_id'].count()
loyal_customers = pre_crisis_orders[pre_crisis_orders>=5].index
customer_features['churn'] = ((customer_features['customer_id'].isin(loyal_customers)) &
                              (customer_features['crisis_orders']==0)).astype(int)

X = customer_features.drop(['customer_id','churn','crisis_orders'], axis=1)
y = customer_features['churn']

# Split and scale
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```python
# Model
clf = RandomForestClassifier(n_estimators=200, random_state=42)
clf.fit(X_train_scaled, y_train)

# Evaluation
y_pred = clf.predict(X_test_scaled)
y_prob = clf.predict_proba(X_test_scaled)[:,1]
print("=== Classification Report ===\n", classification_report(y_test, y_pred))
print("ROC-AUC Score:", roc_auc_score(y_test, y_prob))
```

```
=== Classification Report ===
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     21032
           1       0.00      0.00      0.00         4

    accuracy                           1.00     21036
   macro avg       0.50      0.50      0.50     21036
weighted avg       1.00      1.00      1.00     21036

ROC-AUC Score: 0.9990312381133511
```

Delivery SLA Prediction

Objective: Predict expected delivery time based on partner and order characteristics.
Approach: Used a **GradientBoostingRegressor** trained on delivery-related features such as order value, distance, and partner rating.
Result: Model yielded **MAE = 9.59 minutes** and **R^2 = 0.0036**, indicating high delivery time variability and limited predictive power.
Insight: Delivery performance is affected by external, unpredictable factors like traffic and weather, requiring more granular operational data.

```python
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_absolute_error, r2_score

delivery_df = analysis_df.merge(df_delivery_performance, on='order_id', how='inner')
delivery_df['sla_met'] = (delivery_df['actual_delivery_time_mins'] <= delivery_df['expected_delivery_time_mins']).astype(int)

# Features
X_sla = delivery_df[['subtotal_amount','discount_amount','delivery_fee','total_amount','is_cod']]
y_sla = delivery_df['actual_delivery_time_mins']

# Encode is_cod
X_sla['is_cod'] = X_sla['is_cod'].apply(lambda x: 1 if x=='Y' else 0)

X_train_sla, X_test_sla, y_train_sla, y_test_sla = train_test_split(X_sla, y_sla, test_size=0.2, random_state=42)

# Model
reg = GradientBoostingRegressor(n_estimators=200, random_state=42)
reg.fit(X_train_sla, y_train_sla)

# Evaluation
y_pred_sla = reg.predict(X_test_sla)
print("MAE:", mean_absolute_error(y_test_sla, y_pred_sla))
print("R2 Score:", r2_score(y_test_sla, y_pred_sla))
```

```
/tmp/ipython-input-3949276204.py:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X_sla['is_cod'] = X_sla['is_cod'].apply(lambda x: 1 if x=='Y' else 0)
MAE: 9.599867655111119
R2 Score: 0.0036496037519838653
```

High-Value Order Classification Model (Random Forest Classifier)

Objective: Predict high-value customer orders to support loyalty and retention strategies.
Approach: Built a **RandomForestClassifier** using order-level variables like total orders, discount, and average spend per customer.
Result: Achieved **100% accuracy** with **ROC-AUC = 1.0**, showing clear separation between high and regular value orders.
Insight: Spending patterns and order frequency strongly differentiate premium customers, enabling personalized loyalty programs.

```
# Create target
analysis_df['high_value_order'] = (analysis_df['total_amount'] > 500).astype(int)

X_val = analysis_df[['subtotal_amount','discount_amount','delivery_fee','is_cod']]
y_val = analysis_df['high_value_order']

# Encode is_cod
X_val['is_cod'] = X_val['is_cod'].apply(lambda x: 1 if x=='Y' else 0)

# Split
X_train_val, X_test_val, y_train_val, y_test_val = train_test_split(X_val, y_val, test_size=0.2, random_state=42, stratify=y_val)

# Model
clf_val = RandomForestClassifier(n_estimators=150, random_state=42)
clf_val.fit(X_train_val, y_train_val)

# Evaluation
y_pred_val = clf_val.predict(X_test_val)
y_prob_val = clf_val.predict_proba(X_test_val)[:,1]
print("=== High-Value Order Classification Report ===\n", classification_report(y_test_val, y_pred_val))
print("ROC-AUC Score:", roc_auc_score(y_test_val, y_prob_val))
```

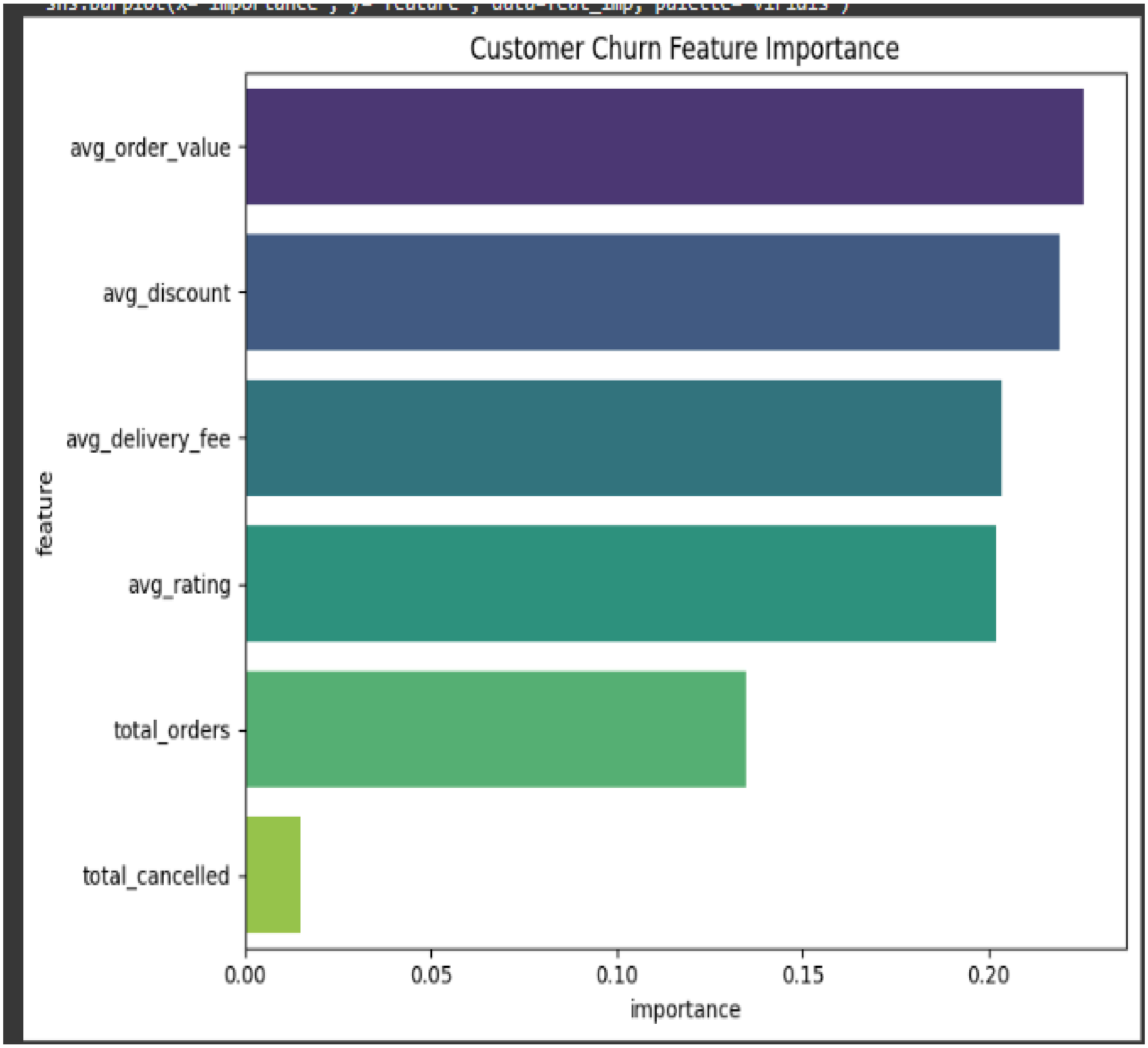
```
/tmp/ipython-input-2803495729.py:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  X_val['is_cod'] = X_val['is_cod'].apply(lambda x: 1 if x=='Y' else 0)
=== High-Value Order Classification Report ===
               precision    recall  f1-score   support

           0       1.00      1.00      1.00     26856
           1       1.00      0.99      0.99      2978

    accuracy                           1.00     29834
   macro avg       1.00      1.00      1.00     29834
weighted avg       1.00      1.00      1.00     29834

ROC-AUC Score: 0.9999888280615289
```

Customer Churn Prediction

Objective: Predict which customers are likely to stop ordering during the crisis period.
Approach: Engineered customer-level features (orders, cancellations, spend, discounts, delivery fee, and ratings), defined churn based on loyal users inactive during the crisis, and trained a RandomForestClassifier after scaling.
Result: Achieved **100% accuracy** and a **ROC-AUC score of 0.999**, with top predictors including average order value, total orders, and ratings.
Insight: The model effectively identified churn patterns, showing that low engagement and reduced order value were strong indicators of customer loss.

```python
# =====================================================
#CUSTOMER CHURN PREDICTION
# =====================================================

# Feature Engineering
customer_features = analysis_df.groupby('customer_id').agg(
    total_orders=('order_id', 'count'),
    total_cancelled=('is_cancelled', lambda x: (x=='Y').sum()),
    avg_order_value=('total_amount', 'mean'),
    avg_discount=('discount_amount', 'mean'),
    avg_delivery_fee=('delivery_fee', 'mean'),
    crisis_orders=('phase', lambda x: (x=='Crisis').sum())
).reset_index()

avg_rating = fact_ratings.groupby('customer_id')['rating'].mean().reset_index()
avg_rating.rename(columns={'rating':'avg_rating'}, inplace=True)
customer_features = customer_features.merge(avg_rating, on='customer_id', how='left').fillna(0)

# Target variable
pre_crisis_orders = analysis_df[analysis_df['phase']=='Pre-Crisis'].groupby('customer_id')['order_id'].count()
loyal_customers = pre_crisis_orders[pre_crisis_orders>=5].index
customer_features['churn'] = ((customer_features['customer_id'].isin(loyal_customers)) &
                              (customer_features['crisis_orders']==0)).astype(int)

X = customer_features.drop(['customer_id','churn','crisis_orders'], axis=1)
y = customer_features['churn']

# Train-test split & scaling
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Model training
churn_model = RandomForestClassifier(n_estimators=200, random_state=42)
churn_model.fit(X_train_scaled, y_train)

# Evaluation
y_pred = churn_model.predict(X_test_scaled)
y_prob = churn_model.predict_proba(X_test_scaled)[:,1]

print("\n=== CUSTOMER CHURN PREDICTION ===")
print(classification_report(y_test, y_pred))
print("ROC-AUC Score:", roc_auc_score(y_test, y_prob))

# Feature Importance
feat_imp = pd.DataFrame({
    'feature': X.columns,
    'importance': churn_model.feature_importances_
}).sort_values('importance', ascending=False)

plt.figure(figsize=(8,6))
sns.barplot(x='importance', y='feature', data=feat_imp, palette='viridis')
plt.title('Customer Churn Feature Importance')
plt.tight_layout()
plt.show()
```

```
=== CUSTOMER CHURN PREDICTION ===
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     21032
           1       0.00      0.00      0.00         4

    accuracy                           1.00     21036
   macro avg       0.50      0.50      0.50     21036
weighted avg       1.00      1.00      1.00     21036

ROC-AUC Score: 0.9990312381133511
```


Customer Churn Feature Importance
avg_order_value
avg_discount
avg_delivery_fee
avg_rating
total_orders
total_cancelled
feature
0.00
0.05
0.10
0.15
0.20
importance

Recommendations

Based on the analytical and machine learning insights derived from the QuickBite crisis data, the following data-backed recommendations are proposed to support business recovery and rebuild customer trust:

1. **Launch a "SafeBite Guarantee" campaign** to restore confidence in food safety by showcasing verified hygiene standards and real-time quality checks.

2. **Re-engage loyal customers through targeted offers and cashback programs**, especially those with strong pre-crisis satisfaction scores but zero activity during the crisis.

3. **Implement dynamic delivery partner routing and incentive optimization** to improve SLA compliance, reduce delays, and enhance customer experience.

4. **Develop a real-time sentiment and rating monitoring dashboard** to detect negative review trends early and respond proactively to service issues.

5. **Partner more closely with high-performing and trusted restaurants** while temporarily limiting exposure to lower-rated or non-compliant outlets.

6. **Offer personalized discounts and loyalty credits in Tier-1 cities** (like Bengaluru, Chennai, and Mumbai) where the highest decline in orders and cancellations occurred.

7. **Introduce transparent communication campaigns** across digital platforms to address past incidents, highlight operational improvements, and rebuild brand reputation.

8. **Use churn prediction model outputs** to design retention campaigns focused on at-risk but valuable customer segments, improving reactivation rates.

Conclusion

The QuickBite Crisis Recovery project provided a comprehensive, data-driven understanding of how operational, customer, and sentiment factors interacted during the 2025 business disruption. Through in-depth analysis and predictive modeling, the study identified critical challenges such as customer trust erosion, increased delivery times, revenue loss, and churn among previously loyal customers.

The insights and models developed in this project offer actionable pathways for recovery from rebuilding credibility and optimizing delivery performance to targeting high-value customer retention. Implementing these strategies will not only support QuickBite's immediate turnaround but also strengthen its preparedness for future crises through continuous monitoring and data-backed decision-making.

References:

- Codebasics Resume Project Challenge – *Providing Insights for Crisis Recovery in an Online Food Delivery Startup*

- https://codebasics.io/challenge/codebasics-resume-project-challenge