

AI-Agentic Supply Chain Analytics

Improving Reliability & Fulfillment Visibility at Atliq Mart

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Executive Summary

This project presents the design, implementation, and validation of an AI-agentic supply chain analytics system for Atliq Mart, an organic food manufacturer operating across India and the United States.

Following geographic expansion into the U.S. market, Atliq Mart experienced declining fulfillment reliability, increased customer dissatisfaction, and limited analytical visibility into supply chain performance. Existing reporting processes—largely dependent on Excel files and manually processed CSVs received via email—proved inadequate for diagnosing operational issues at scale or supporting timely decision-making.

To address these challenges, an end-to-end analytics solution was designed using agentic automation (n8n), cloud-native data storage and modeling (PostgreSQL on Supabase), and AI-assisted analytics (Quadratic AI). The system automated data ingestion, standardized operational data across regions, and enabled rapid, prompt-driven business analysis—while explicitly retaining human-in-the-loop validation for business-critical metrics such as On-Time In-Full (OTIF).

1. Client Context

Atliq Mart is a Gujarat-based organic food manufacturer supplying packaged organic products to large supermarket chains. After establishing a strong domestic presence in India, the company expanded operations into the United States to capitalize on growing demand for organic food products.

While sales volumes increased post-expansion, the supply chain infrastructure did not mature at the same pace. Operational inefficiencies surfaced in order fulfillment, delivery reliability, and inventory planning. These issues were particularly visible in the U.S. market, where customers operate under strict Service Level Agreements (SLAs) and expect consistently high fulfillment standards.

The Chief Operating Officer identified unreliable order management, lack of fulfillment visibility, and delayed decision-making as strategic risks threatening customer retention and commercial negotiations.

2. Business Problem

The client faced four interrelated supply chain challenges that collectively constrained performance and scalability.

2.1 Customer Dissatisfaction

Supermarket customers reported:

- Late deliveries
- Partial order fulfilment
- Inconsistent service reliability

Even isolated fulfilment failures had a disproportionate impact due to SLA penalties and reputational risk, threatening long-term customer relationships.

2.2 Lack of Inventory & Fulfillment Visibility

The organization lacked reliable, standardized metrics to answer fundamental operational questions:

- Are orders being delivered on time?
- Are orders being delivered in full?
- Which customers, products, or regions are driving failures?

Key KPIs such as **On-Time Delivery**, **In-Full Delivery**, and **OTIF** were either unavailable or inconsistently calculated, preventing leadership from diagnosing whether failures stemmed from inventory shortages, planning gaps, or logistics execution issues.

2.3 Fragmented Data Landscape

Operational data arrived daily via email as CSV attachments and was fragmented across:

- Geography (India vs USA)
- Granularity (order-level vs order-line data)
- Format (inconsistent schemas and date representations)

Processing was manual, error-prone, and non-scalable, making analytical accuracy dependent on individual effort rather than system design.

2.4 Need for Modern, Scalable Analytics

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3. Project Objectives

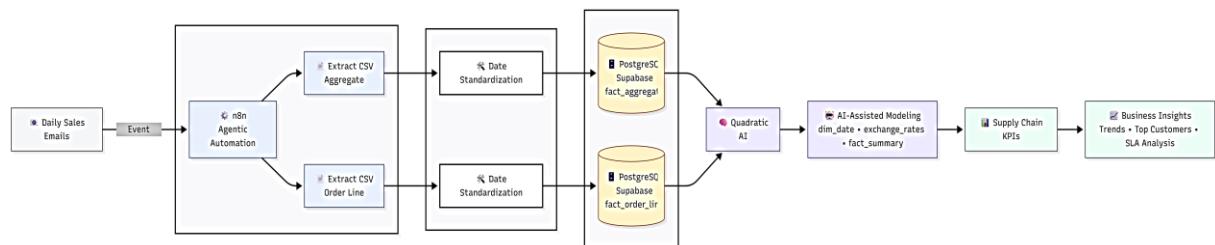
The project aimed to design and implement an **AI-agentic supply chain analytics system** that would:

- Automate ingestion of daily sales data received via email
- Centralize India and USA operations into a unified analytical environment
- Compute industry-correct supply chain KPIs
- Enable fast, prompt-driven business analysis using AI
- Improve fulfilment reliability before further geographic expansion

4. End-to-End Architecture Overview

A modern, layered analytics architecture was designed with explicit separation of responsibilities:

- **Agentic Automation Layer** – n8n (local deployment)
- **Data Storage & Modelling Layer** – PostgreSQL (Supabase)
- **Analytics & AI Layer** – Quadratic AI
- **Validation Layer** – Human-in-the-loop review

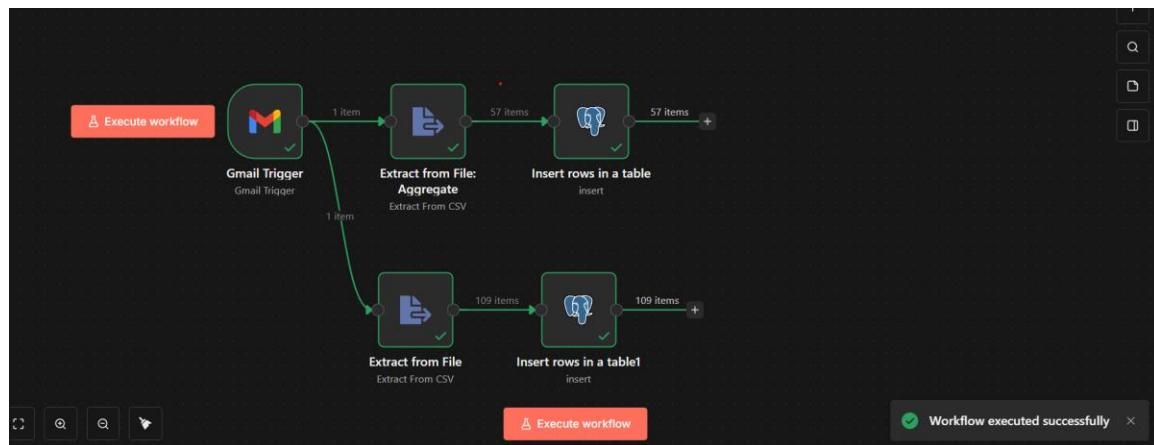


5. Data Ingestion & Agentic Automation (n8n)

An event-driven automation workflow was implemented using **n8n (local deployment)** to eliminate manual data handling.

Key Automation Steps

- Monitor Gmail inbox for emails with subject “**daily sales**”
- Automatically download CSV attachments
- Separate:
 - Aggregate order data
 - Order-line level data
- Standardize inconsistent date formats using **Luxon**
- Ingest cleaned data into PostgreSQL tables hosted on Supabase



This automation reduced ingestion latency, minimized human error, and created a repeatable operational pipeline.

6. Data Modeling & Storage (PostgreSQL on Supabase)

A centralized PostgreSQL database served as the **single source of truth** for analytics.

Key Design Principles

- Clear separation of **fact** and **dimension** tables
- Preservation of correct data grain:

- Order-level (fact_aggregate)
- Line-level (fact_order_line)
- Region-agnostic schema supporting both India and USA operations

This modelling approach ensured accurate KPI computation, prevented double counting, and enabled scalable multi-region analysis.

7. AI-Assisted Analytics (Quadratic AI)

Quadratic AI was used as the analytics and exploration layer, connected directly to PostgreSQL. Using **natural language prompts**, Quadratic AI was leveraged to:

- Generate a **date dimension table**
- Create a **historical exchange rate table** using the OpenExchangeRates API
- Build a denormalized **fact_summary** table for exploration
- Compute supply chain KPIs
- Generate charts and analytical tables on demand

The screenshot shows a Microsoft Excel spreadsheet titled "Fact_Summary". The table contains data from March 1, 2025, with columns: order_id, order_pla..., customer..., city, product_id, product_n..., category, order_qty, and agreed_delivery_d. The code editor panel on the right shows the following Python code:

```

1 import pandas as pd
2 import numpy as np
3 # ① Load data
4 # -----
5 # fact_order_line is a table (Postgres5)
6 # orders = q.cells("Postgres5")
7 # dim_products is a sheet range: skip
8 # first row, use second row as headers
9 # products = n cells
10 # Line 209 returned DataFrame on Jan 27, 2026

```

Table: fact_summary

8. KPI Framework & Logic

A robust KPI framework was established using industry-standard supply chain definitions and strict grain control.

The screenshot shows a PostgreSQL query editor interface. On the left, a table titled 'Postgres6' displays seven KPI metrics. The columns are 'kpi_name' and 'kpi_value'. The rows include: Total Orders (13652), Total Order Lines (24530), Line Fill Rate (65.95%), Volume Fill Rate (96.60%), On Time Delivery (59.28%), In Full Delivery (52.94%), and On Time In Full (29.04%). The timestamp Jan 27, 2026 is also present. On the right, the raw SQL code for generating these metrics is shown:

```
1 WITH line_level_metrics AS (
2   SELECT
3     COUNT(*) AS total_order_lines,
4     COUNT(DISTINCT order_id) AS
5     total_orders,
6     SUM(order_qty::numeric) AS
7     total_qty_ordered,
8     SUM(delivery_qty::numeric) AS
9     total_qty_delivered,
10    SUM(
11      CASE
12        WHEN
```

Below the code, a note states: "Returned 2x7 Array in 1227ms on Jan 27, 2026".

8.1 Total Orders

Definition: Count of unique customer orders.

Formula: Count(DISTINCT Order_ID).

Grain: Order level.

8.2 Total Order Lines

Definition: Count of individual line items.

Formula: Count(rows in order-line table).

Grain: Line level.

8.3 Line Fill Rate (LFR)

Definition: Percentage of order lines delivered in full.

Formula: (Lines Delivered in Full ÷ Total Order Lines).

Grain: Line level.

8.4 Volume Fill Rate (VFR)

Definition: Percentage of total ordered quantity delivered.

Formula: (Total Delivered Quantity ÷ Total Ordered Quantity).

Grain: Quantity level.

8.5 On-Time Delivery (OT)

Definition: Orders delivered on the agreed delivery date.

Formula: (On-Time Orders ÷ Total Orders).

Grain: Order level.

8.6 In-Full Delivery (IF)

Definition: Orders delivered with 100% quantity across all lines.

Logic: Any shortfall in any line fails the order.

Formula: (In-Full Orders ÷ Total Orders).

Grain: Order level.

8.7 On-Time In-Full (OTIF)

Definition: Orders delivered both On-Time and In-Full.

Formula: (Orders OT AND IF ÷ Total Orders).

Grain: Order level.

9. Business Insights Generated

9.1 Monthly On-Time Performance by City



Monthly On-Time Delivery Performance by City (Line Chart)

Revealed regional performance variation, emerging reliability trends, and early warning signals for intervention.

9.2 Top Customers by Order Value & Reliability

	I	J	K	L	M	N	O
1	Python9						
2	Customer...	Customer...	City	Total Ord...	OTIF %	IF %	OT %
3	789320	Whole Foods	New Jersey, US	48,799,930	36.5	58.4	70.4
4	789301	Foodtown	New Jersey, US	48,682,351	30.8	56.6	68.6
5	789420	Lidl	New Jersey, US	48,450,607	22	68.3	28.7
6	789401	Wegmans	New Jersey, US	47,694,192	35.7	54.9	72
7	789101	Costco Wholes	New Jersey, US	47,370,701	35.5	56	71.2

Top 5 Customers – OTIF, IF %, OT % Table

Enabled customer prioritization, SLA discussions, and targeted corrective actions.

10. Human-in-the-Loop Validation

AI outputs were **not blindly trusted**.

All results were reviewed for:

- KPI definition correctness
- Proper data grain usage
- Business-safe interpretation

This prevented silent analytical errors and ensured long-term trust.

11. Impact

The solution:

- Eliminated manual CSV handling
- Improved visibility into fulfilment failures
- Accelerated decision-making
- Established a scalable analytics foundation

Leadership shifted from reactive explanations to **data-driven root-cause analysis**.

12. Key Learnings & Takeaway

AI is a force multiplier — not a replacement for analytical thinking.

When combined with domain expertise, disciplined modelling, and validation, AI-agentic systems significantly improve supply chain reliability.

Appendix

Appendix A: Date Standardization Logic

Luxon was used within n8n to normalize inconsistent date formats into ISO format prior to database insertion.

Appendix B: KPI Grain & Validation Strategy

Order-level and line-level KPIs were computed separately to avoid aggregation errors and ensure business correctness.

Appendix C: SQL Validation

Final KPIs were cross-validated using SQL Common Table Expressions to verify AI-generated outputs.

Appendix D: AI Prompt Governance

AI prompts were explicitly structured and all outputs manually reviewed.

Appendix E: Limitations & Future Enhancements

Limitations include partial US automation and retrospective analysis. Future enhancements include predictive OTIF modeling, SLA alerts, and inventory optimization.