OFI

CASE STUDY- NexGen Logistics

OPTION-8: Delay Root Cause & Cost Impact Analyser

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1. Business Problem & Context

NexGen Logistics manages diverse shipments across India and nearby international hubs.
With expanding order volume and route complexity, delivery timelines are increasingly unpredictable.

Unplanned delays trigger multiple business challenges:

- higher operational costs
- customer dissatisfaction and churn risk
- poor fleet utilization
- difficulty forecasting resources

Currently, decision-making relies on after-the-fact performance reports rather than predictive insights.
There is a clear opportunity to use data and machine learning to anticipate risks and optimize routing decisions proactively.

2. Key Observations from Data Exploration

After integrating datasets on orders, delivery performance, fleet, routes, and cost, important patterns emerged:

- Delays correlate strongly with high traffic congestion windows and longer routes
- Older fleet assets assigned to extended trips elevate failure probability
- Transport costs increase sharply when shipment delays exceed a time threshold
- Certain warehouses consistently show higher delay incidence, indicating systemic inefficiencies
- Overhead and vehicle maintenance expenses vary unexpectedly, signaling potential cost anomalies

These insights point toward the need for a tool that not only predicts delay likelihood but also identifies drivers influencing costs.

3. Proposed Solution

I built a lightweight logistics intelligence platform that combines:

- **machine learning delay prediction**
- **interactive dashboards for operational insights**
- **cost impact forecasting tools**
- **root cause and efficiency analysis**

It gives planners and managers the ability to explore trade-offs, simulate outcomes, and take preventative action rather than being reactive.

The prototype runs locally, requires no external services, and is built entirely in Python and Streamlit.

4. System Components & Architecture

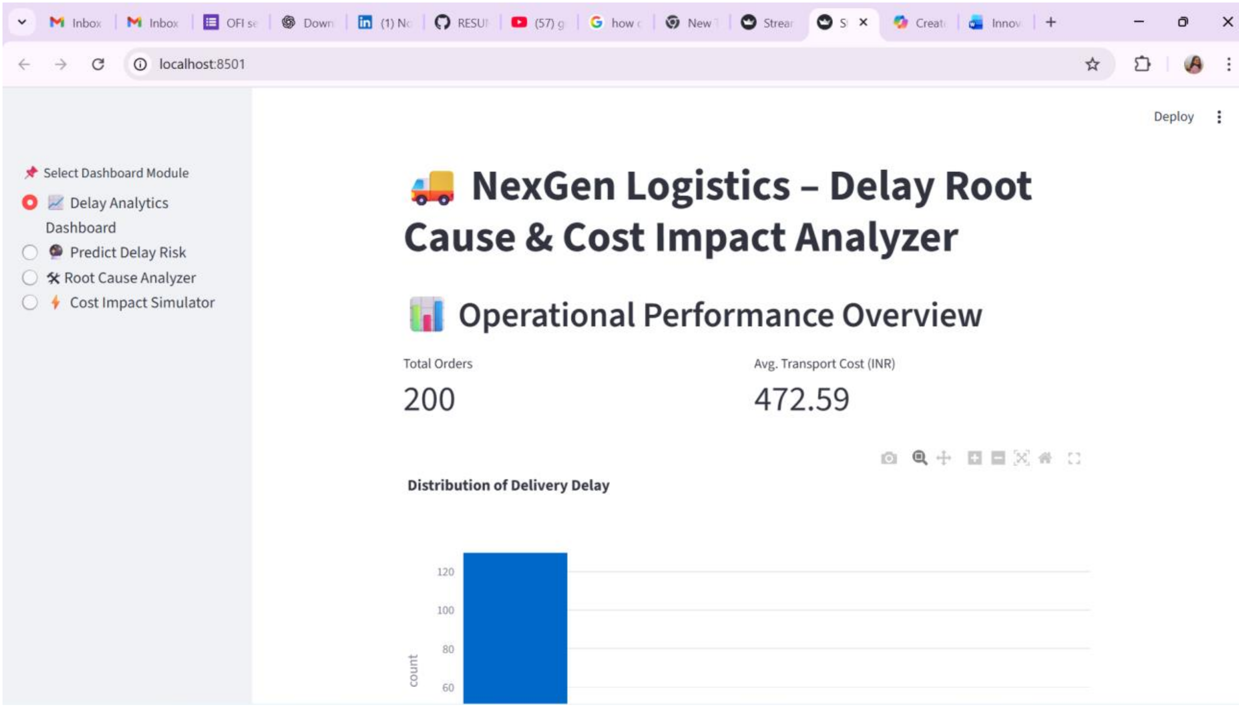
The end-to-end workflow includes:

1. Data ingestion and cleaning from multiple operational datasets
2. Feature engineering for:
    a. delay severity
    b. route efficiency
    c. cost anomaly scoring
3. Random Forest-based delay prediction model
4. Model export for fast inference
5. Processed dataset export for dashboard use
6. Streamlit web application for decision support

Outputs include visual analytics, predictions, and cost estimations through a user-friendly interface.

Figure 1 – Delay Analytics Overview

Displays overall shipment volume and baseline transport cost, along with distribution of delivery delay across orders.



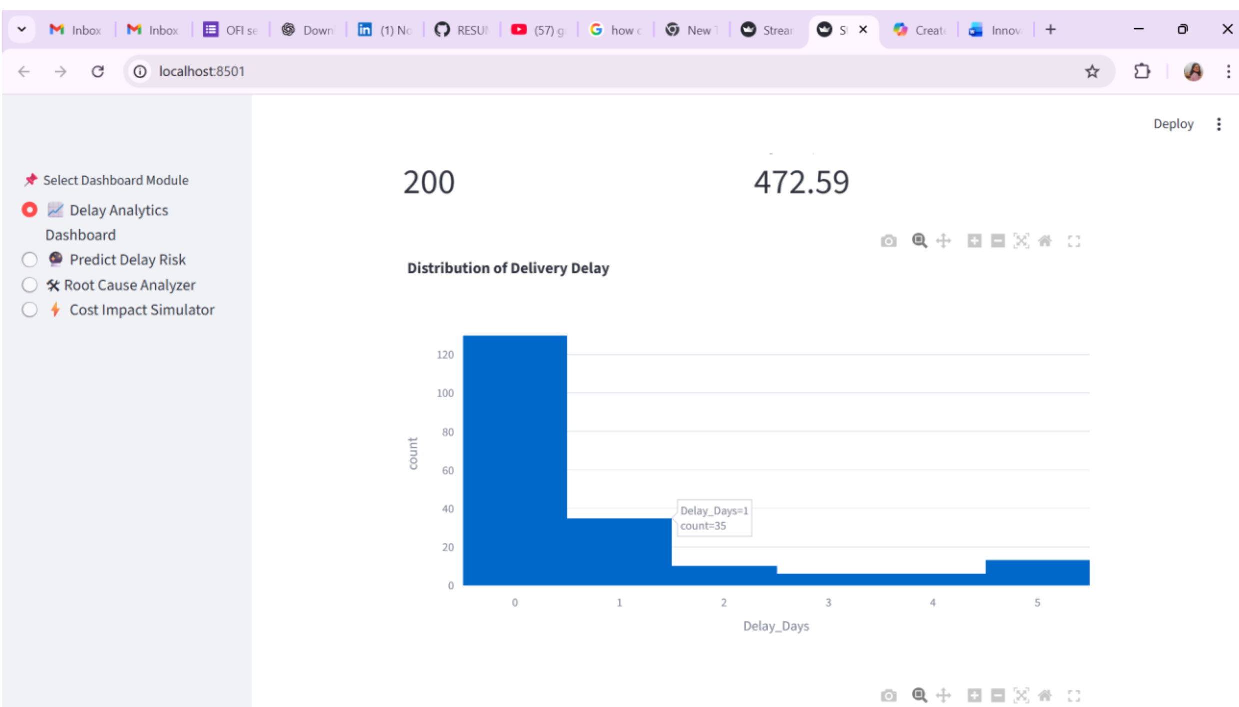


Figure 2 – Cost–Delay Interaction

Interactive visualization showing how operational delay duration influences total transport cost and anomaly flags for outliers.

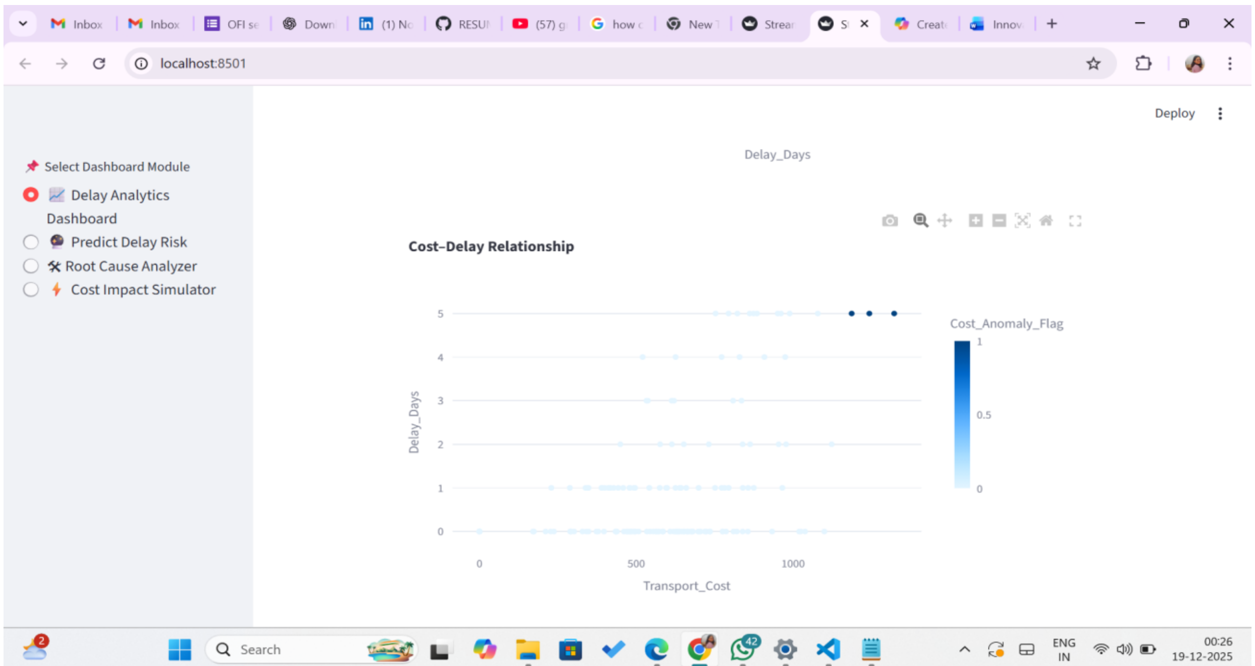


Figure 3 – Route Efficiency Explorer

Users analyze route performance using computed Route Efficiency Index, highlighting where operational improvements are required.

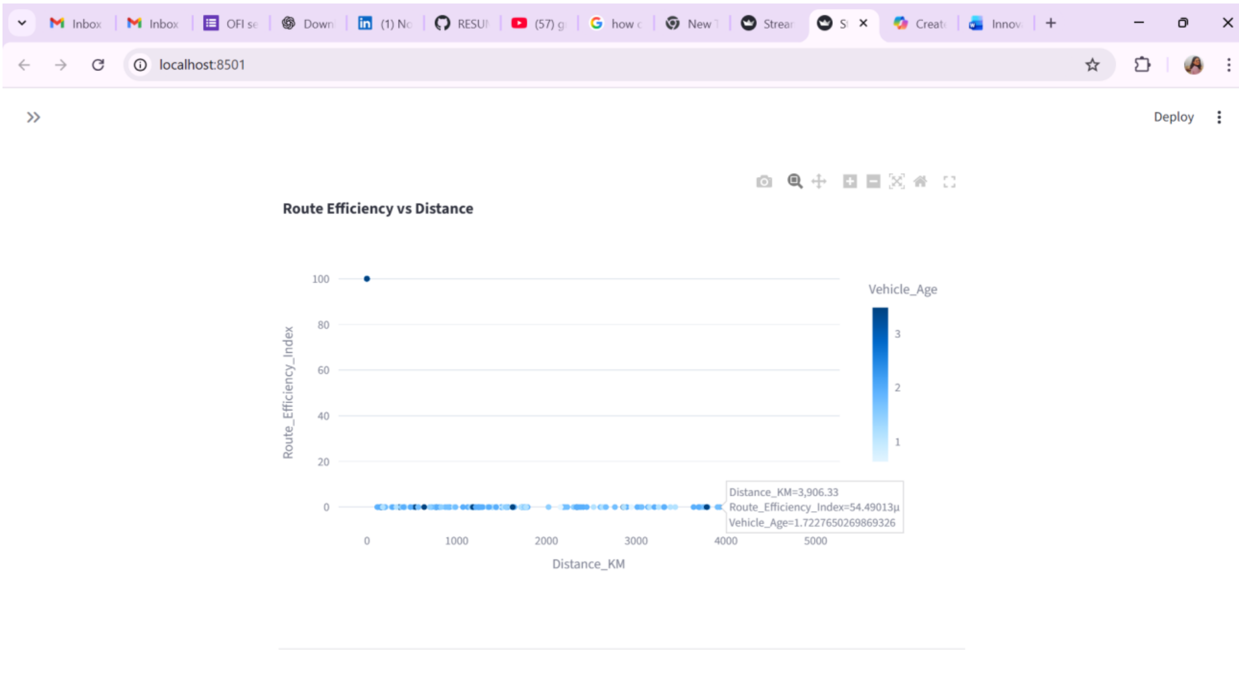


Figure 4 – Delay Risk Predictor

Users input operational variables (transport cost, delay severity score, vehicle age etc.) to obtain predicted delay probability.

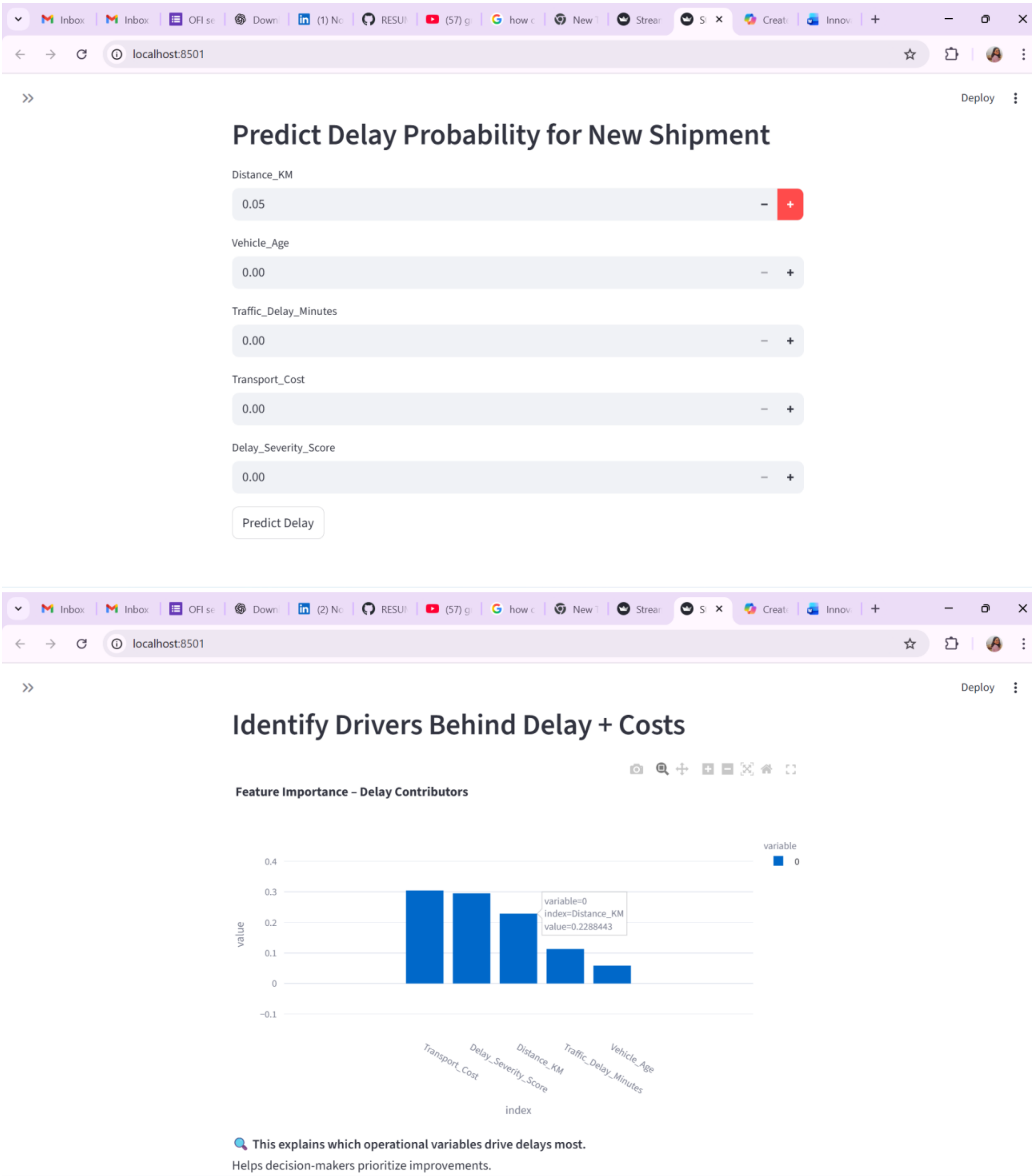
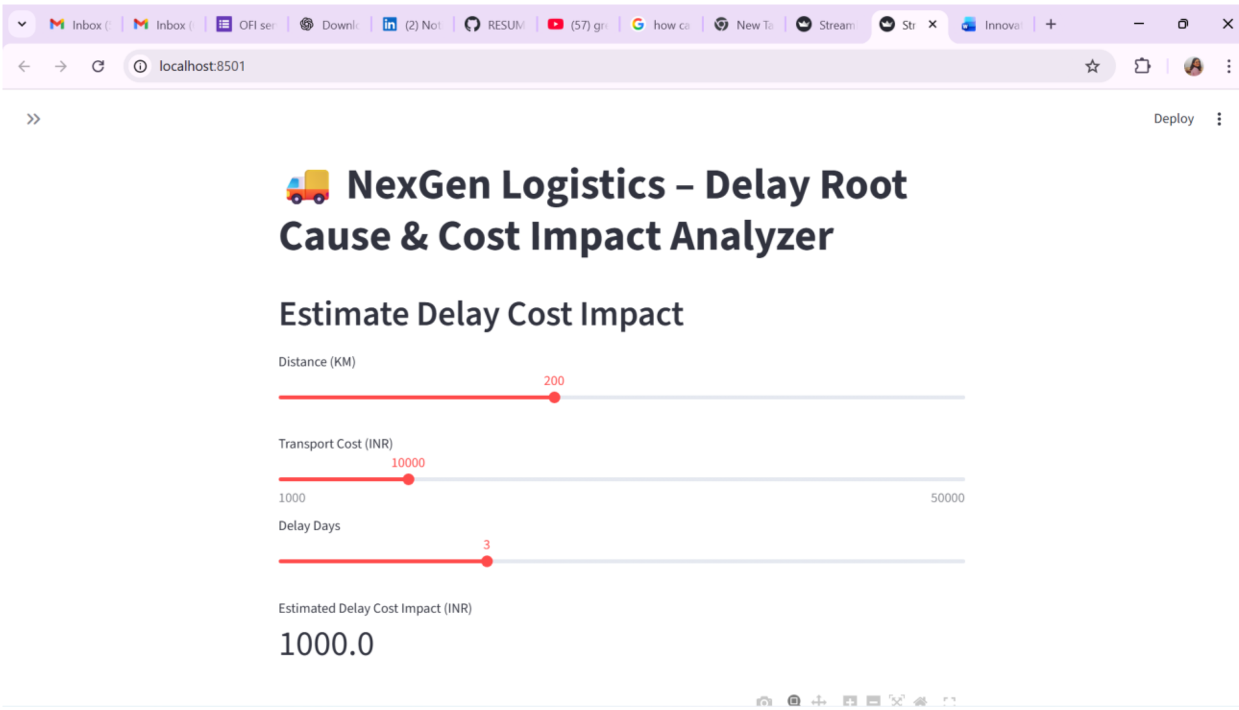
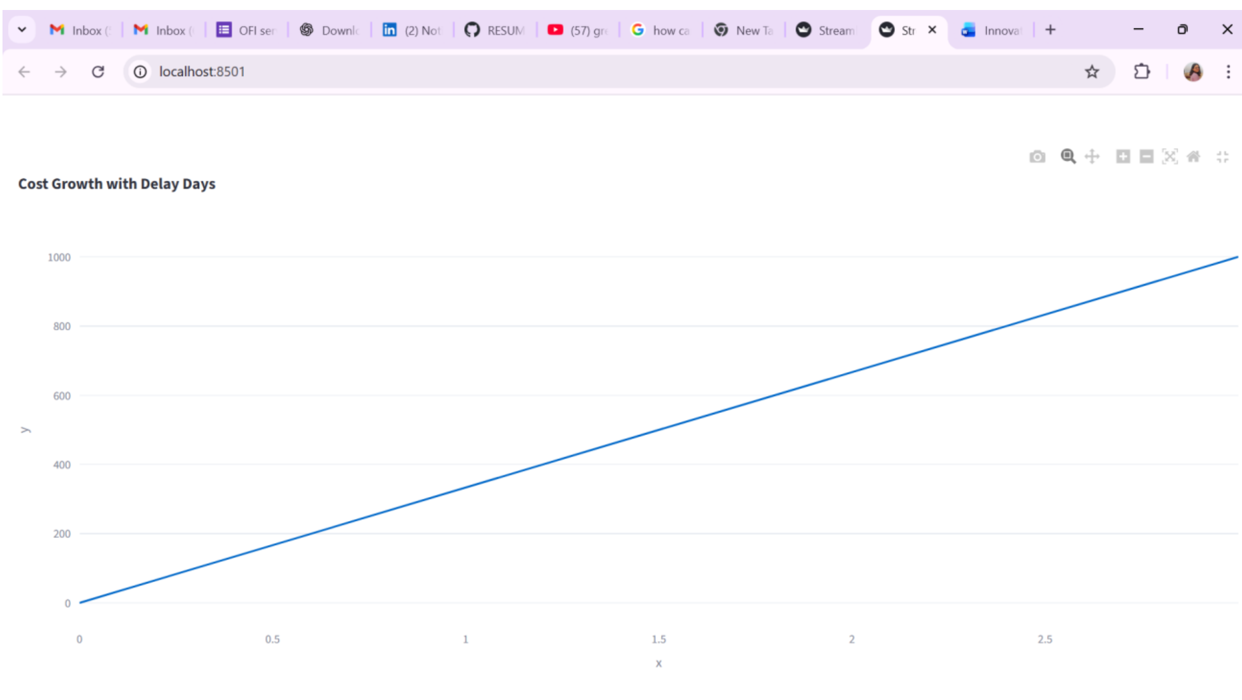


Figure 5 – Delay Cost Impact Simulator

Simulates estimated loss from varying delay durations and projected cost growth.





5. Core Capabilities Delivered

Capability	Business Value
Delay Risk Prediction	enables proactive intervention
Root-Cause Analysis	exposes operational weaknesses
Cost Impact Simulator	supports budget-aware routing
Route Efficiency Index	improves fleet deployment strategy
Interactive Visual Dashboard	assists faster decisions

6. Potential Business Impact

The tool supports meaningful improvements across logistics KPIs:

- reduced late deliveries and penalties
- better control over transport costs
- improved fleet and route utilization
- visibility into inefficiencies and hidden expenses
- smarter planning and dispatch schedules

Even modest improvements compound significantly across high shipment volumes.

7. Roadmap for Future Development

If extended beyond prototype stage, next-phase enhancements could include:

- dynamic fleet scheduling optimization
- real-time data ingestion from IoT / GPS telemetry
- predictive maintenance models for fleet longevity

- carbon cost routing for sustainability optimization

Conclusion

The proposed platform demonstrates how combining machine learning, descriptive analytics, and interactive reporting can transform logistics planning from reactive problem-solving to proactive strategic decision-making.

This working prototype can be scaled into a production-level decision intelligence product with meaningful potential ROI for NexGen Logistics.