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AI Agentic Supply Chain Intelligence System: Real-Time GPS Tracking, ETA and Delay Prediction, and AI-Driven Recommendations for Logistics Monitoring

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Abstract: Online shopping, global trade and expanding transportation networks have made logistics monitoring a central concern for modern businesses. Most vehicle-tracking systems only show where a vehicle is at a given moment; they do not predict delays, estimate arrival times reliably, or support decisions. This leads to higher costs, late deliveries and unhappy customers. This paper presents the AI Agentic Supply Chain Intelligence System, a web-based platform that combines real-time GPS tracking, route visualization, estimated time of arrival (ETA) prediction, machine-learning-based delay prediction, fleet monitoring and AI-generated recommendations in one dashboard. The system analyses vehicle location, route distance, traffic level and weather risk, and uses Random Forest regression to forecast shipment delays. The platform is built with Python, FastAPI, Scikit-Learn, OpenStreetMap, OpenRouteService, HTML, CSS, JavaScript and Leaflet.js. A working prototype was developed and validated through eight functional test cases covering tracking, routing, ETA, delay prediction, fleet monitoring, recommendations, analytics and reporting, all of which passed. The results show that combining geospatial technologies with predictive analytics improves supply chain visibility and supports faster, better-informed logistics decisions.

Index Terms: Supply Chain Intelligence, GPS Tracking, ETA Prediction, Delay Prediction, Random Forest, Route Visualization, Fleet Monitoring, FastAPI, OpenStreetMap, AI Recommendation

I. INTRODUCTION

Logistics and supply chain management ensure that goods reach the right place at the right time. As online shopping grows and transportation networks expand, companies must handle large numbers of shipments, vehicles and delivery routes every day. Managing this manually is difficult and often causes delays, higher costs and reduced efficiency [1]. Artificial Intelligence (AI) and Machine Learning (ML) can analyse logistics data, find patterns, predict delays, estimate arrival times and suggest ways to make transportation more efficient. GPS tracking and mapping technologies additionally let organizations watch vehicle movements in real time and evaluate how routes perform. This paper presents the AI Agentic Supply Chain Intelligence System, which integrates GPS tracking, route visualization, ETA estimation, delay prediction, fleet monitoring and AI recommendations into one platform for logistics managers.

A. Motivation

Logistics operations generate large volumes of data about vehicle positions, shipment status, routes and delivery schedules. Conventional tracking systems only report current positions. They lack delay prediction, ETA estimation, route optimization and decision support, so managers struggle to anticipate disruptions caused by traffic or weather and to monitor many vehicles at once. The absence of analytics and intelligent recommendations reduces operational efficiency and weakens supply chain performance.

B. Main Contributions

The main contributions of this work are:

- A unified platform combining real-time GPS tracking, route visualization, fleet monitoring and shipment status in one dashboard
- ETA prediction based on route distance, traffic conditions and transportation data
- A Random Forest regression model for forecasting shipment delays from logistics-related factors
- An AI recommendation module that converts route conditions and delay predictions into actionable suggestions, such as rerouting during heavy traffic

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- A lightweight web implementation using open geospatial services (OpenStreetMap and OpenRouteService) that runs on a standard personal computer
- Functional validation of the complete pipeline through eight integrated test cases

II. RELATED WORK

A. GPS-Based Vehicle Tracking

GPS vehicle tracking is widely used by logistics and transportation companies to know where vehicles and shipments are at any time, which improves fleet visibility and delivery tracking. However, traditional tracking systems show only current positions; they cannot forecast what may happen next or support decision-making.

B. Machine Learning for Delay Prediction

Machine learning has been applied to predict transportation delays and arrival times using models such as Random Forest regression and decision trees [3]. Such models learn from transportation data and help logistics companies plan better, although their accuracy depends on data quality and availability.

C. Mapping and Route Planning

OpenStreetMap [4], [7] and OpenRouteService [8] support route planning, navigation and distance calculation. Vehicle routing research [2] offers methods for efficient route construction, but many route-planning systems offer limited real-time operational intelligence.

D. Intelligent Logistics Monitoring Platforms

Recent platforms combine GPS tracking, predictive analytics and dashboards to give managers a live view of logistics operations. Many of them still lack advanced AI-based decision support.

E. Gap in Existing Systems

Table I summarizes existing approaches. No single approach combines tracking, route visualization, ETA prediction, delay prediction and AI recommendations in one platform.

TABLE I
COMPARISON OF EXISTING APPROACHES

Approach	Advantage	Limitation
GPS vehicle tracking	Real-time location monitoring	No delay prediction or recommendations
ML delay prediction	Predicts delays, improves planning	Depends on data quality
Route planning systems	Efficient routes, less travel time	Limited real-time intelligence
Fleet monitoring platforms	Better fleet visibility	Lacks AI decision support
AI-based supply chain mgmt.	Better decisions and efficiency	Needs large datasets and compute
Proposed system	Tracking, routing, ETA, delay prediction and recommendations in one dashboard	Prototype stage; sample dataset

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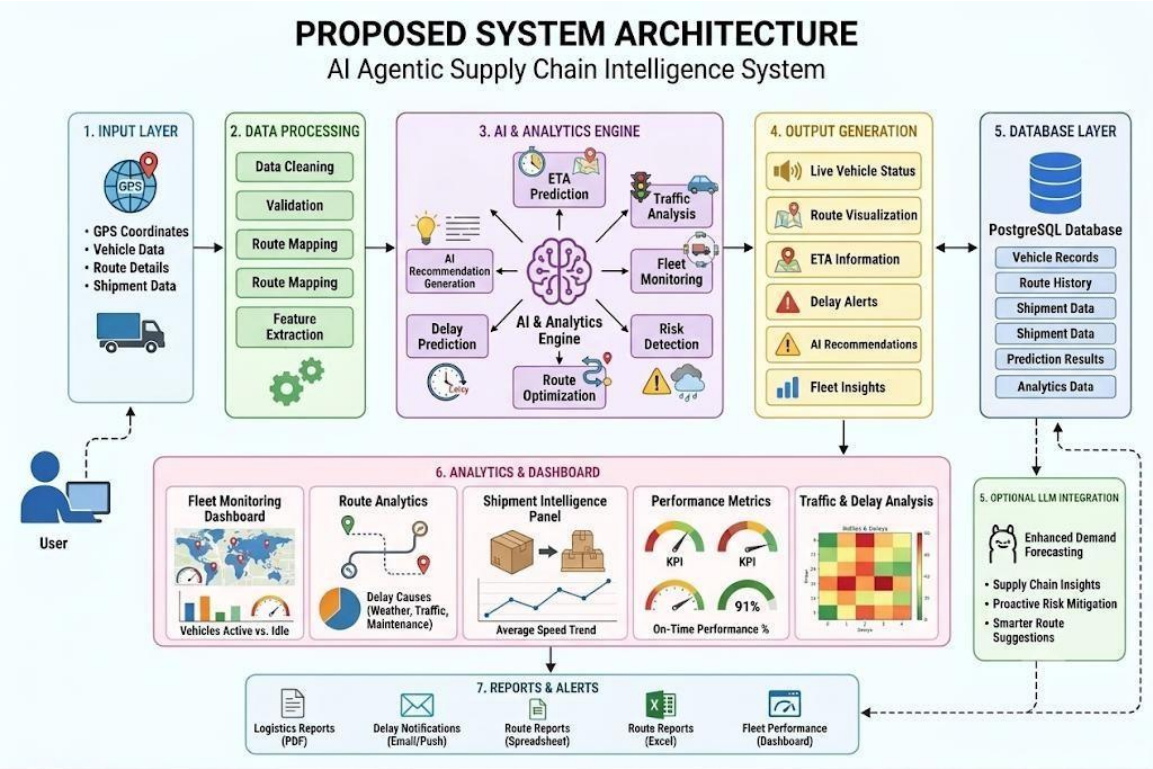


Fig. 1. Proposed system architecture of the AI Agentic Supply Chain Intelligence System.

III. SYSTEM ARCHITECTURE

A. Layered Architecture

The system follows a layered architecture, shown in Fig. 1, consisting of seven stages: (1) an *input layer* receiving GPS coordinates, vehicle data, route details and shipment data; (2) *data processing* for cleaning, validation, route mapping and feature extraction; (3) an *AI and analytics engine* performing ETA prediction, delay prediction, traffic analysis, fleet monitoring, risk detection, route optimization and recommendation generation; (4) *output generation* of live vehicle status, route visualization, ETA information, delay alerts and fleet insights; (5) a *database layer* holding vehicle records, route history, shipment data, prediction results and analytics data; (6) an *analytics dashboard*; and (7) *reports and alerts*. An optional LLM integration layer supports demand forecasting, supply chain insights, proactive risk mitigation and smarter route suggestions.

B. Technology Stack

Table II lists the technologies used. The backend exposes REST endpoints through FastAPI [6], the delay model is implemented with Scikit-Learn [5], and routes are drawn on an interactive Leaflet.js map [9].

TABLE II
SYSTEM TECHNOLOGY STACK

Component	Technology
Backend	Python, FastAPI
Machine learning	Scikit-Learn (Random Forest)
Mapping and routing	OpenStreetMap, OpenRouteService
Frontend	HTML, CSS, JavaScript, Leaflet.js
Storage	Database for vehicle, route and prediction records
Development	Visual Studio Code, Windows 10/11

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C. Hardware Requirements

The system runs on a standard personal computer: Intel Core i3/i5/i7 or higher, 8 GB RAM or more, 50 GB of free storage and an internet connection for map services and optional LLM integration. No specialized hardware is required.

IV. METHODOLOGY

The overall workflow is: collect GPS location, route and shipment data; validate and preprocess it; analyse route distance, traffic and transportation status; apply the ML model for ETA and delay prediction; generate route insights and AI recommendations; display results on the dashboard; store results in the database; and generate reports and analytics.

A. Dataset

The project uses a logistics and transportation dataset assembled from GPS tracking data, route information and shipment records, stored as structured data. Its main fields are listed in Table III, together with delay status, shipment status and recommendations.

TABLE III
DATASET FEATURES

Feature	Description
Vehicle ID	Unique vehicle identifier
Current Location	Real-time GPS coordinates
Destination	Delivery destination
Route Distance	Total travel distance
Traffic Condition	Road congestion information
Weather Condition	Environmental factors affecting transport
ETA	Estimated time of arrival

B. GPS Tracking Algorithm

The tracking algorithm (1) collects GPS coordinates from the tracked vehicle, (2) validates the location data, (3) updates the vehicle position, (4) displays the position on the map and (5) stores the tracking information in the database. This gives real-time monitoring, improved fleet visibility and better shipment tracking.

C. Route Distance Calculation

The distance between two coordinates is computed with the Haversine formula using Earth radius R = 6371 km:

$$a = \sin^2(\Delta\varphi/2) + \cos\varphi_1 \cos\varphi_2 \sin^2(\Delta\lambda/2) \qquad (1)$$

$$d = 2R \cdot \operatorname{atan2}(\sqrt{a}, \sqrt{(1-a)}) \qquad (2)$$

where φ is latitude and λ is longitude in radians. Road routes are obtained from OpenRouteService; if the routing service is unavailable, the system falls back to a simple intermediate-point route so that the dashboard keeps working.

D. ETA Prediction Algorithm

The ETA algorithm collects route distance and vehicle information, analyses traffic and transportation conditions, calculates the estimated travel time, predicts the arrival time and displays it on the dashboard. Conceptually,

$$ETA = T_{now} + D_{rem} / v_{eff} \qquad (3)$$

where D*rem* is the remaining route distance and v*eff* is the effective speed, reduced as the traffic level rises.

E. Random Forest Delay Prediction

Delay prediction uses Random Forest regression [3], an ensemble of decision trees whose outputs are averaged:

$$\hat{y} = (1/T) \Sigma_{t=1..T} h_t(x) \qquad (4)$$

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where T is the number of trees, h*t* is the t-th tree and x is the feature vector (route distance, traffic level, weather risk and related factors). The steps are: collect transportation and route data, normalize it, train the model, predict shipment delays, and generate delay alerts and recommendations. Random Forests handle mixed numerical features well, resist overfitting through averaging and are efficient on moderately sized datasets.

F. AI Recommendation Algorithm

The recommendation module analyses route and shipment information, evaluates the delay prediction, identifies transportation risks, generates suggestions and displays them on the dashboard. For example, when the traffic level is high and a delay is predicted, the module recommends an alternative route to reduce the ETA.

V. IMPLEMENTATION

The system is organized into three modules. Module 1, *Fleet Tracking and Route Management*, retrieves vehicle and shipment information, collects and updates GPS coordinates, draws routes on an interactive map, calculates distance and duration, and monitors shipment status. A browser-based GPS test page confirms that the device latitude and longitude can be read and displayed. Module 2, *AI Prediction and Analytics*, analyses transportation data with ML algorithms to predict delays, estimate ETA, evaluate transportation performance and generate recommendations, storing results for monitoring and historical analysis. Module 3, *Dashboard and Reporting*, compiles analysis results into dashboards, alerts and downloadable logistics reports.

VI. RESULTS AND DISCUSSION

A. Experimental Setup

The prototype was run on a standard personal computer (Windows 10/11, 8 GB RAM) with an internet connection for map and routing services, using the prepared logistics dataset of vehicle records, route information, shipment details, traffic conditions and transportation data.

B. Prototype Output

The dashboard (Fig. 2) shows summary indicators for active trucks, delayed shipments, AI confidence and system status. In the demonstration run it reported 5 active trucks, 1 delayed shipment, 91% AI confidence and an ACTIVE system status. Table IV lists the fleet snapshot displayed by the dashboard.

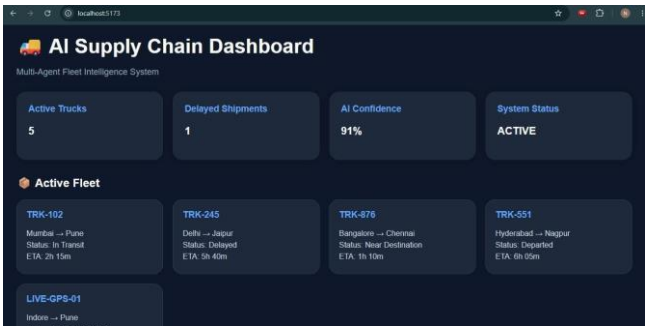


Fig. 2. AI Supply Chain Dashboard showing key indicators and the active fleet.

TABLE IV
FLEET SNAPSHOT FROM THE DASHBOARD

Vehicle	Route	Status	ETA
TRK-102	Mumbai → Pune	In Transit	2h 15m
TRK-245	Delhi → Jaipur	Delayed	5h 40m
TRK-876	Bangalore → Chennai	Near Destination	1h 10m
TRK-551	Hyderabad → Nagpur	Departed	6h 05m
LIVE-GPS-01	Indore → Pune	Live Tracking	Calculating

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For a live-tracked vehicle, the Shipment Intelligence panel (Table V) reported a delayed shipment over a 624.06 km route with a traffic level of 9/10, and recommended rerouting via the Nashik highway. On successive refreshes the values varied slightly (for example ETA 17h 20m, confidence 0.91 and weather risk 1), reflecting the changing inputs. The route was drawn on an OpenStreetMap base layer with start and destination markers (Fig. 3).

TABLE V
SHIPMENT INTELLIGENCE PANEL OUTPUT

Field	Value
Status	DELAYED
ETA	17h 10m
Distance	624.06 km
Delay cause	Traffic and weather AI prediction
Truck status	Near destination
AI confidence	0.93
Traffic level	9/10
Weather risk	0
AI recommendation	Heavy traffic detected; reroute via Nashik highway to reduce ETA

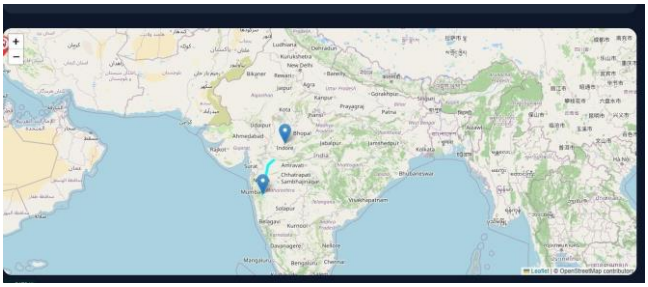


Fig. 3. Route visualization on an OpenStreetMap base layer using Leaflet.js.

C. Functional Testing

After integrating all modules, complete system testing was performed. All eight test cases passed (Table VI).

TABLE VI
OVERALL MODULE TESTING

Test Case	Expected Result	Status
GPS Tracking	Vehicle location updated	Passed
Route Visualization	Route displayed correctly	Passed
ETA Prediction	ETA generated	Passed
Delay Prediction	Delay forecast generated	Passed
Fleet Monitoring	Vehicle status displayed	Passed
AI Recommendation	Suggestions generated	Passed
Analytics Dashboard	Transportation statistics generated	Passed
Report Generation	Logistics report created	Passed

D. Discussion

The prototype shows that tracking, routing, prediction and recommendation can be delivered through one lightweight web platform on ordinary hardware. Moving from passive tracking to predictive monitoring gives operators early warning of delays and a concrete suggested action rather than only a map of vehicle positions. Using open services keeps deployment cost low.

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E. Limitations

- The current evaluation is functional; large-scale quantitative validation (for example MAE, RMSE and R^2) on real fleet data is planned for the next stage
- Prediction accuracy depends on the quality and quantity of available data
- Traffic and weather inputs are simplified indicators rather than live feeds
- Routing and map services require an internet connection
- The dataset is a prepared sample set rather than a long-running production stream

VII. FUTURE WORK

- Integration of live weather and traffic APIs
- Cloud deployment for large-scale, multi-fleet operation
- Integration with IoT devices and intelligent transportation systems
- Evaluation on larger real-world datasets with reported error metrics
- Comparison with advanced models such as gradient boosting and deep learning
- LLM-based demand forecasting and natural-language explanation of recommendations
- Mobile application for drivers and managers

VIII. CONCLUSION

This paper presented the AI Agentic Supply Chain Intelligence System, a platform that brings together real-time GPS tracking, route visualization, ETA estimation, Random Forest delay prediction, fleet monitoring and AI recommendations. By combining geospatial technologies with machine learning, the system improves supply chain visibility and supports faster, more informed decisions. All integrated test cases passed in the prototype, and the architecture is open to extension with live data sources, cloud deployment and more advanced models.

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