Delivery Delay Analysis and Predictive Modeling Across Global Markets

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December 2025

Outline

Research Background

- Global supply chains face continuous change, uncertainty, and reconfiguration due to:
    - Wars and geopolitical tensions
    - Tariff policies
    - Increasing complexity in global logistics
- Delivery reliability is a key indicator of:
    - Logistics service quality
    - Customer satisfaction
    - Competitive advantage
- High delivery delay rates increase costs and damage firm reputation.

Role of Digital Tools

- Digital tools such as:
  - Machine Learning
  - Artificial Intelligence (AI)
  - Scenario modeling

  support:
  - Real-time visibility
  - Better forecasting
  - Data-driven decision-making
- Digitization in supply chains includes digital products, services, and process management (Büyüközkan & Göçer, 2018).

Research Question

Main Research Question

How can companies analyze and predict delivery delays using machine learning across global markets?

- Combine descriptive analytics and machine learning.
- Provide both visibility and predictive capability for supply chain decisions.

Transportation Disruptions and Delays

- Transportation disruption is a critical supply chain risk (Wilson, 2006).
- Consequences:
  - Late deliveries
  - Operational shutdowns
  - Lost sales
  - Reputational damage (Guiffrida & Jaber, 2008)
- Common delay drivers:
  - Shipment lead time and scheduling accuracy
  - Carrier performance and transportation mode
  - Operational bottlenecks in fulfillment centers
  - Order-level anomalies (e.g., fraud investigation)

Digital Technologies in Supply Chains

- Predictive analytics transforms transportation from reactive to proactive decisions.
- Deep learning and ML can improve prediction accuracy by 30–45% (Shavaki & Ghahnavieh, 2022).
- Tree-based ensemble models (XGBoost, Random Forest) show strong performance in logistics risk prediction (Mirzaei et al., 2025).
- ML enhances firms' ability to:
    - Detect risks
    - Anticipate disruptions
    - Increase resilience (Cui et al., 2023)

Research Gap and Hypotheses

- Limited research compares delay patterns across multiple global markets *and* integrates ML-based prediction.
- **H1:** What is the relationship between the top five most important features and delivery performance?
- **H2:** What is the relationship between delivery rates in the five markets with the highest delay rates?

Research Design

- Quantitative research design with three main phases:
  1. Descriptive analytics:
     - Compare delivery performance across markets.
  2. Predictive modeling:
     - Logistic Regression (L2)
     - Random Forest
     - XGBoost
  3. Feature importance analysis:
     - Identify key factors influencing delivery delays.

Dataset

- DataCoSupplyChain dataset
- $\sim$ 22,000 records, 20,000 valid orders after cleaning
- Includes:
  - Customer information
  - Order and product details
  - Transportation and shipping information
  - Target label: *Late_delivery_risk* (1 = late, 0 = on time)

Data Preprocessing

- Missing values:
  - Categorical: mode imputation
  - Numerical: mean imputation
- Leakage variables removed:
  - Delivery status
  - Scheduled and actual shipping days
  - Shipping dates
- Encoding and scaling:
  - One-Hot Encoding for categorical variables
  - StandardScaler for numerical variables

Models and Hyperparameters

- **Logistic Regression (L2):**
  - L2 regularization to mitigate multicollinearity
  - High interpretability
- **Random Forest:**
  - 300 trees
  - Gini impurity as splitting criterion
- **XGBoost:**
  - $n\_estimators = 250$
  - $learning\_rate = 0.1$
  - $max\_depth = 5$
  - $subsample = 0.8$

Train–Test Split and Metrics

- 80/20 train–test split
- Stratified by *Late_delivery_risk* to preserve class balance
- Evaluation metrics:
  - Accuracy
  - F1 Score
  - AUC (primary metric)
- AUC chosen for robustness and ability to evaluate discriminative performance under class imbalance.

Overall Overview

- 20,000 valid orders
- Overall late delivery rate: **55.2%**
- More than half of shipments miss the scheduled delivery date.

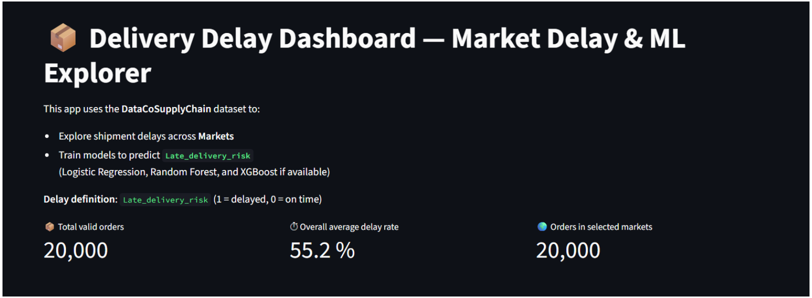

Figure: Overview of Delivery Performance

Delay Rate by Market

Table: Delay Rate by Market

Market	Orders	Delay Rate (%)
Africa	1,279	52.23%
USCA	2,925	53.95%
LATAM	5,749	55.42%
Europe	5,580	55.52%
Pacific Asia	4,467	56.35%

Visualization: Delay by Region

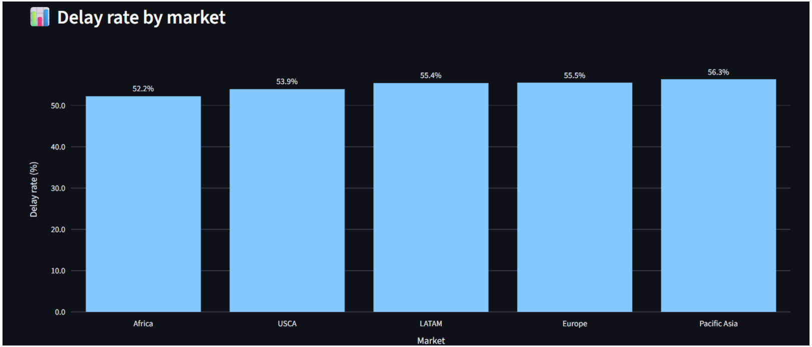

Figure: Delay Rate by Region

Model Performance (80/20 Split)

Table: Model Performance on 80/20 Test Set

Model	Accuracy	F1 Score	AUC
Logistic Regression (L2)	0.738	0.754	0.820
XGBoost	0.712	0.699	0.781
Random Forest	0.726	0.713	0.802

Top 5 Important Features

Table: Top 5 Important Features (Random Forest)

Rank	Feature	Importance
1	Days for shipment (scheduled)	0.0485
2	Shipping Mode — Standard Class	0.0439
3	Shipping Mode — First Class	0.0388
4	Shipping Mode — Second Class	0.0152
5	Order Status — SUSPECTED_FRAUD	0.0127

Feature Importance Plot

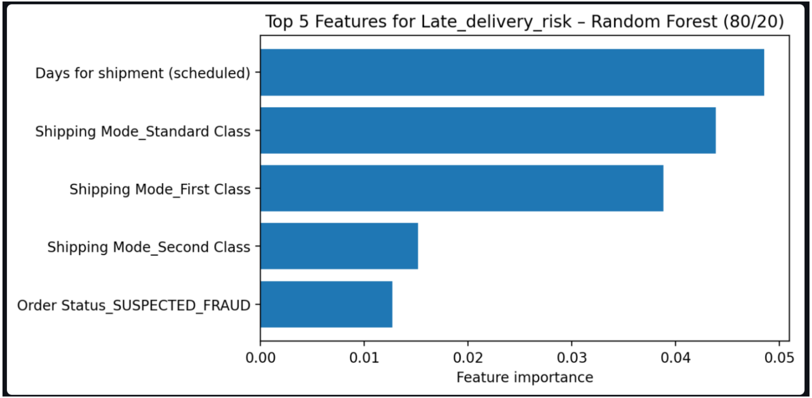

Figure: Top 5 Important Features for Late Delivery Risk

Discussion: Key Insights

- Delay rates above 50% in all markets:
  - Suggest systemic operational inefficiencies.
- Logistic Regression outperforms more complex models:
  - Indicates largely linear and monotonic relationships.
- Feature importance highlights:
  - Planning-related factors (scheduled shipment days)
  - Transportation mode selection
  - Internal processes (fraud screening)

Managerial Implications

- Improve shipment scheduling accuracy:
  - Refine forecasting and resource allocation.
- Optimise shipping mode selection:
  - Align with customer priority and product criticality.
- Strengthen carrier performance monitoring:
  - Consider diversifying logistics partners.
- Integrate ML-based risk detection:
  - Flag high-risk orders before fulfillment.

Limitations and Future Research

- Single-company dataset limits generalizability.
- Missing variables:
  - Geographic distance
  - Carrier ID
  - Weather or disruption data
- Future research:
  - Cross-company comparisons
  - Integration of real-time data (GPS, IoT)
  - Evaluation of additional ML models

Conclusion

- Delivery delays are widespread and systemic across markets.
- Logistic Regression provides strong and interpretable predictive performance.
- Key drivers of delay:
  - Planned shipment duration
  - Shipping mode
  - Fraud-related processes
- ML-based approaches can support:
  - Better planning
  - Smarter transportation decisions
  - Proactive risk management