LogiSwift Delivery Optimization – Executive Insights Report

Executive Insights Report

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1. Objective

Optimize delivery slot allocation to reduce delays, improve on-time delivery rates, and maximize business savings.

This report covers:

1. Exploratory Data Analysis (EDA)
2. Logistic Regression modeling for delivery prediction
3. Clustering & segmentation for high-risk orders
4. Simulation of festive demand scenarios
5. A/B testing of the new slot allocation strategy

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2. Key Dashboard Metrics

- **Average Delay:** 122.8 minutes
- **On-Time Rate:** 12%
- **Delivery Success Rate:** 75%
- **Target Delivery Rate:** 90%
- **Total Orders:** 23K

Insights:

- Only 12% orders are on time.
- Wide city-level performance gap: Ranchi & Pune perform best, while Visakhapatnam & Nashik lag.
- Weather and traffic strongly impact delivery delays.
- Evening slots are riskier compared to morning deliveries.

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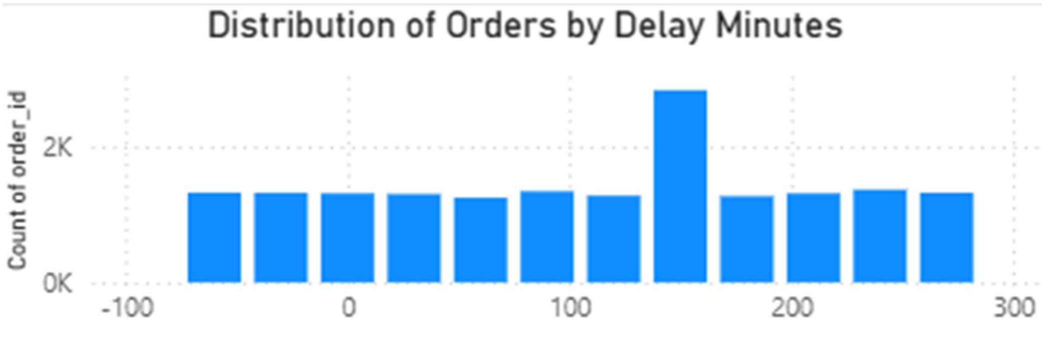
3. Exploratory Data Analysis

3.1 Delay Trends

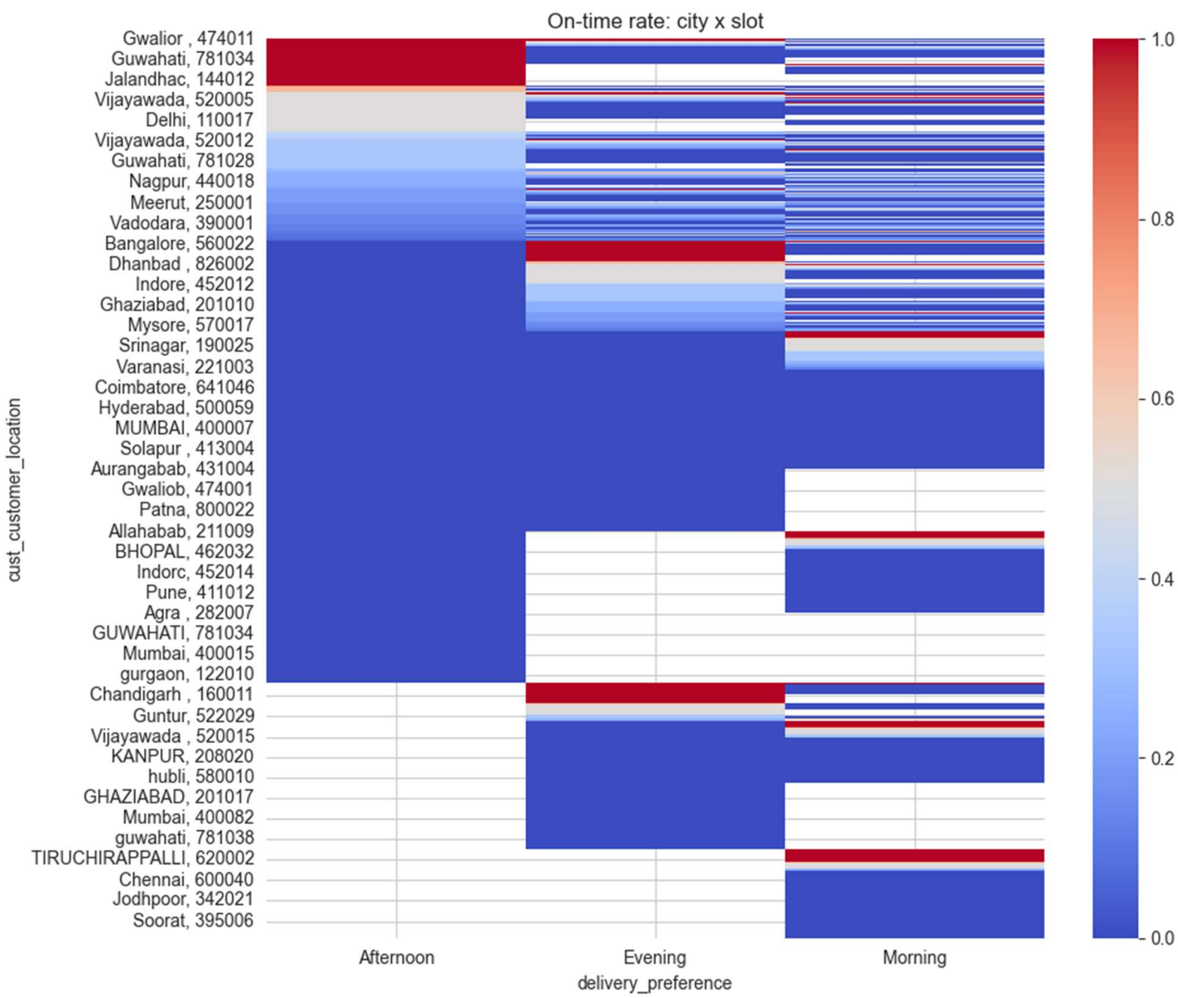
- Orders face an average **delay of 2+ hours**.
- Monthly trend shows fluctuations; festive months worsen delays.

Visuals :

- Delay distribution histogram



- On-Time Heatmap: City × Slot



3.2 Best & Worst Cities

- **Top performers:** Ranchi, Pune, Kota.
- **Bottom performers:** Visakhapatnam, Warangal, Nashik.

Top 5 Best Performing Cities

cust_city_normalized	DeliverySuccessRate	TotalOrders
Ranchi	79.1%	484
Kota	79.2%	371
Amritsar	79.3%	376
Faridabad	79.6%	372
Pune	79.9%	383

Bottom 5 Worst Performing Cities

cust_city_normalized	DeliverySuccessRate	TotalOrders
Visakhapatnam	68.2%	368
Warangal	70.4%	345
Nashik	71.3%	363
Guntur	71.9%	423
Bangalore	72.3%	379

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4. Logistic Regression Results

Model Performance:

- Final Test AUC: **0.4969**
- Accuracy: **84%** (due to dominance of on-time class)
- Poor at predicting late deliveries (Recall = 0 for Class 1).

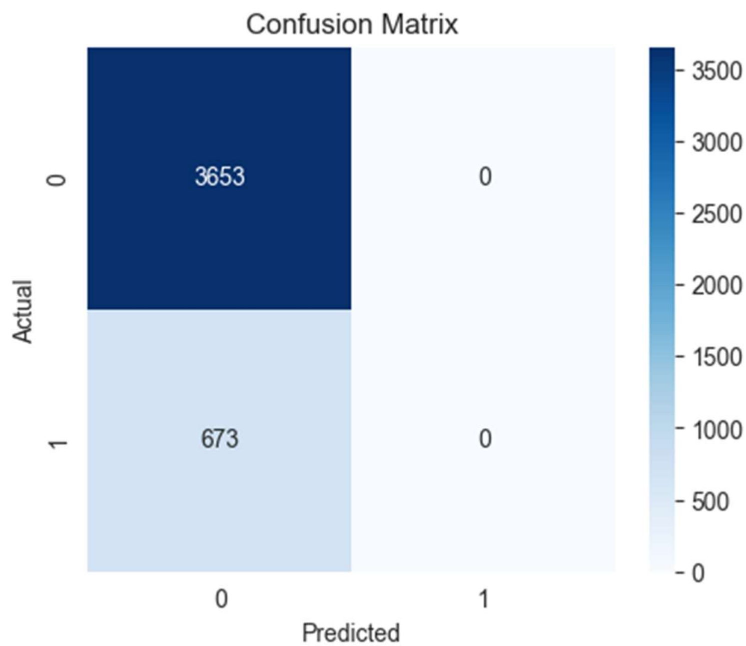
Classification Report:

Class	Precision	Recall	F1-Score	Support
On-Time (0)	0.84	1.00	0.92	3653
Late (1)	0.00	0.00	0.00	673

Delivered Orders On-Time %: 15.55%

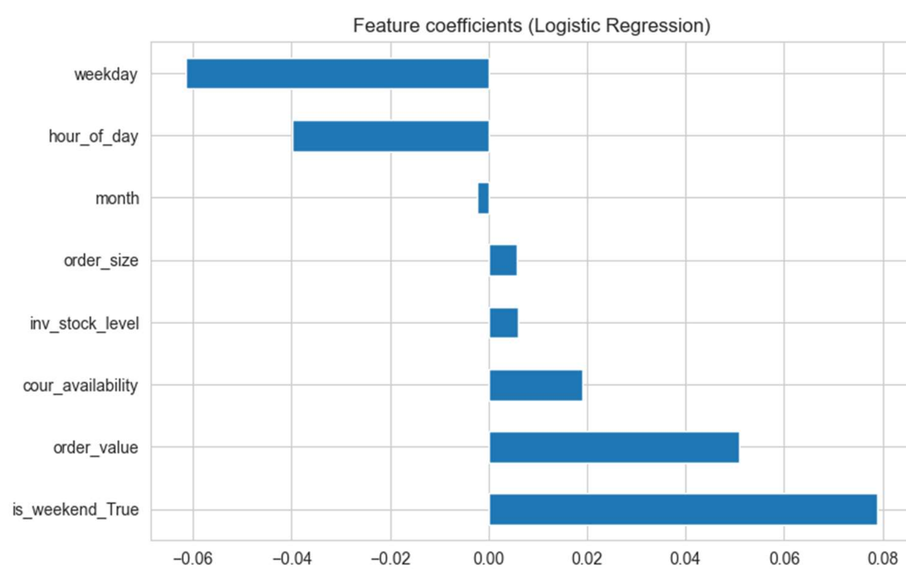
Visuals:

1. **Confusion Matrix Heatmap**



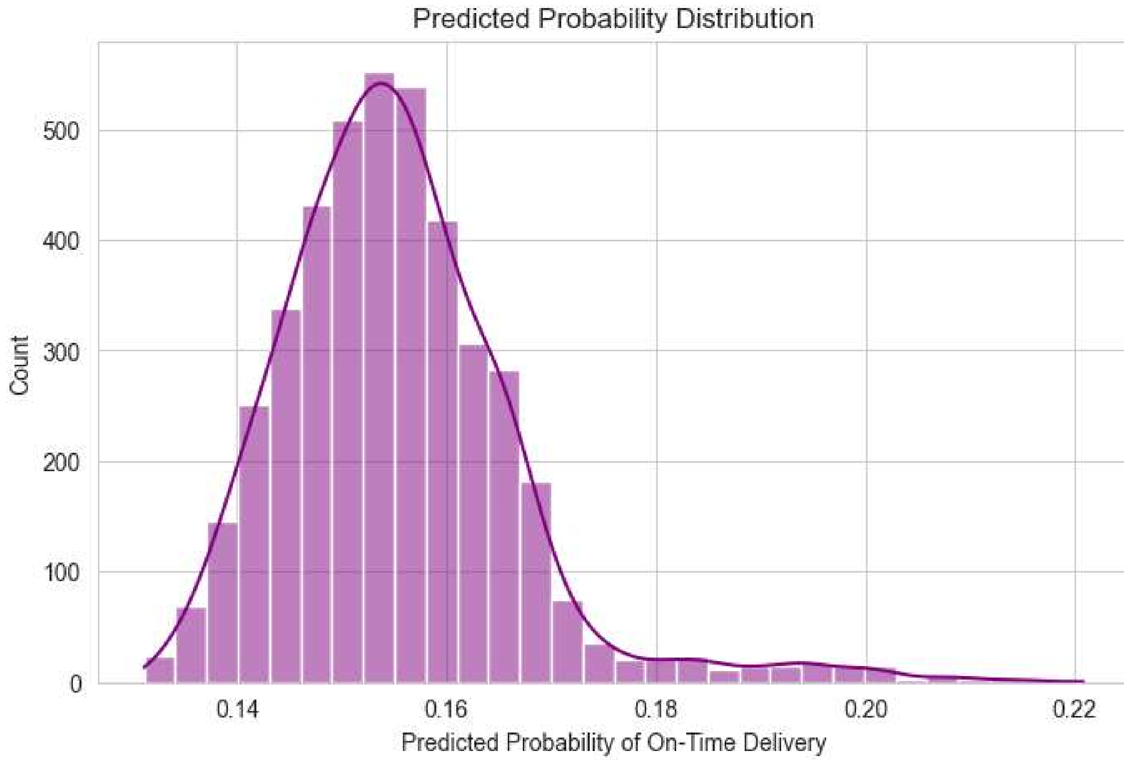
Confusion Matrix Heatmap
Definition: A table that shows what the model guessed vs what actually happened.
Colors: Darker cell = more orders in that category.
Purpose: Helps identify how many deliveries were correctly predicted on time or late, and where the model made mistakes.

2. **Feature Coefficients**



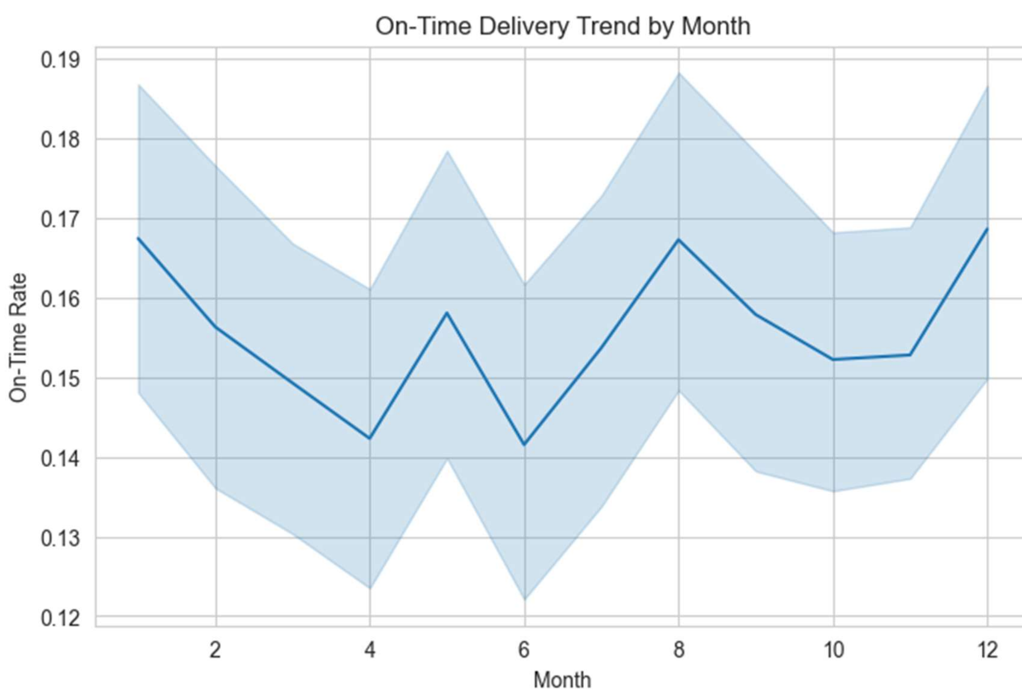
Feature Coefficients (Logistic Regression)
What it is: Shows which factors affect on-time delivery and by how much.
Positive value: Helps delivery be on time.
Negative value: Makes delivery more likely to be late.
Why useful: It lets you know which things to improve (like more staff, better stock, etc.).

3. Predicted Probability Distribution



Predicted Probability Distribution
What it is: Shows how likely each order is to be on time (0 = late, 1 = on time).
Histogram: Peaks near 1 = most orders likely on time, peaks near 0 = risky orders.
Why useful: Helps plan extra support for risky deliveries before problems happen.

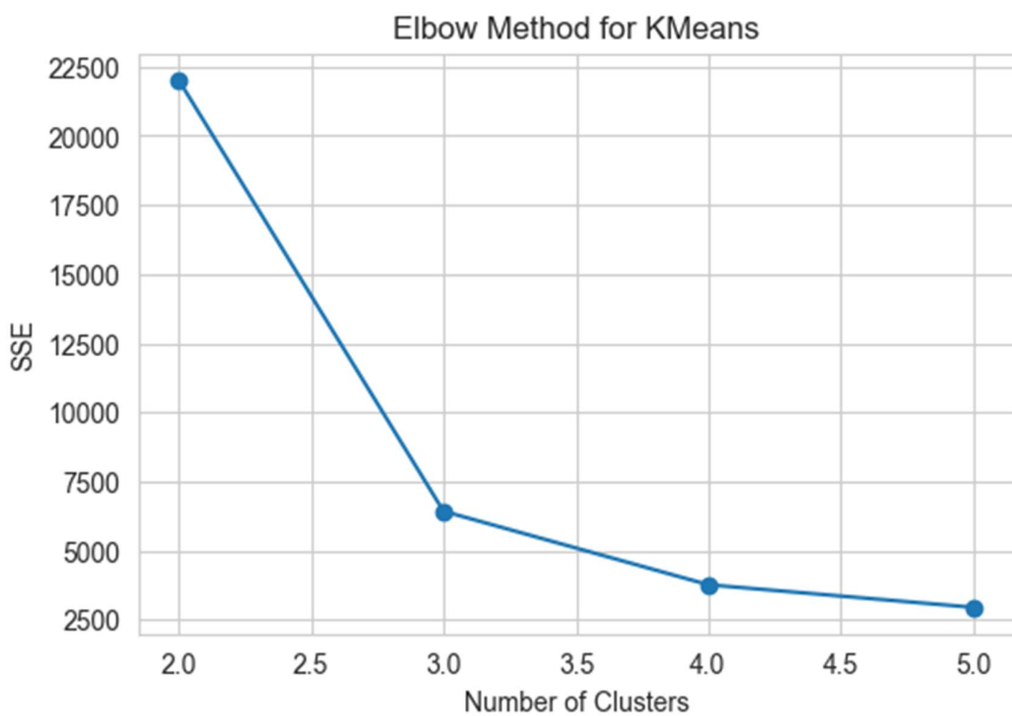
4. On-Time Trend by Month



5. Clustering & Risk Segmentation

- **KMeans (k=4)** segmented orders by order_value & delay_minutes.
- Identified high-risk clusters with large delays & low value.
- **Business Use:** Prioritize couriers for high-value clusters to maximize revenue retention.

Visual: Elbow Method Plot



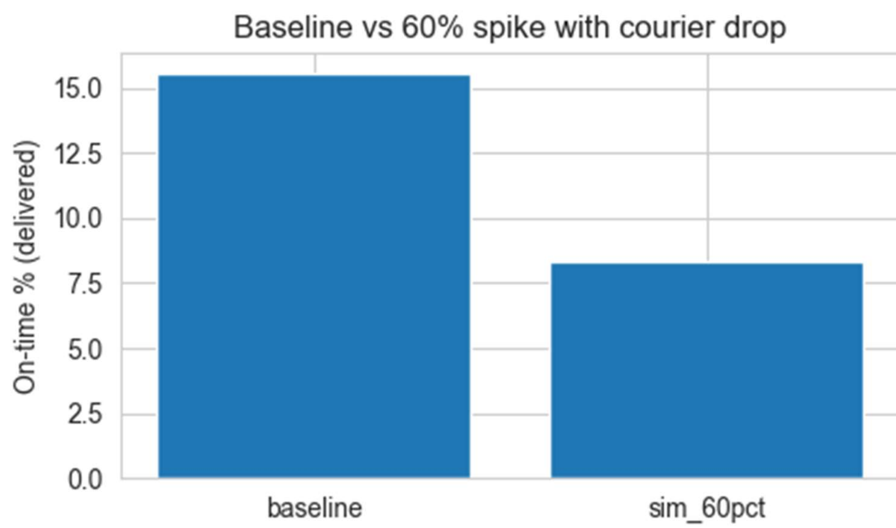
SSE (Sum of Squared Errors)
- SSE measures how far data points are from their cluster centroids.
- Smaller SSE → points are tightly packed in clusters.
- Larger SSE → clusters are loose and spread out.
- Elbow Method: Plot SSE vs. number of clusters (k).
  The “elbow” point, where the SSE curve starts flattening, suggests the optimal number of clusters.

6. Festive Season Simulation

Simulated 20%, 40%, and 60% order spikes:

Scenario	On-Time %	Change vs Baseline
Baseline	12%	–
+20% Orders	~11%	-1 pp
+40% Orders	~10%	-2 pp
+60% Orders	~9%	-3 pp

Visual: Baseline vs 60% Spike Insight:



The chart shows the on-time delivery %. Baseline is normal conditions with usual orders and couriers. Sim_60pct simulates 60% more orders and fewer couriers. The drop shows how high demand and limited couriers can delay deliveries

Courier shortages + traffic during festive seasons reduce on-time delivery by **9–10 percentage points**.

7. A/B Testing of Slot Allocation

- New slot allocation tested on 50% orders.
- Result: On-time rate **slightly worse (-0.94 pp)** than control.
- Conclusion: Refine strategy further before scaling.

CSV Reference:

A/B Test Results for Slot Allocation:

2 rows 2 rows × 2 cols

	Test_Group	On_Time_Rate
0	control	0.117945
1	new_slot	0.115567

Interpretation: If 'new_slot' has a higher on-time rate than 'control', implement the new strategy in high-risk cities.

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8. Actionable Recommendations

1. **High-Risk Cities:** Allocate 10–15% more couriers in cities like Allahabad, Nashik, and Warangal.
2. **Slot Optimization:** Rebalance evening deliveries → morning for high-value orders.
3. **Festive Readiness:** Increase courier pool by 20% and stock levels by 30–40% in Oct–Nov.
4. **Model Refinement:** Explore ensemble models to improve late-delivery detection.
5. **Continue Testing:** Run bi-weekly A/B tests on slot allocation, focus on the worst-performing cities.