

Al-Powered Last Mile Delivery Platform for Urban Logistics

Smarter dispatching through AI-driven route optimization and real-time learning

We developed a full-featured last-mile delivery platform for a European logistics company specializing in bicycle-based deliveries. The system serves major brands like McDonald's, Burger King, and local postal providers, supporting thousands of daily deliveries across several cities. Our solution combines complex B2B integrations, dynamic constraint-based dispatching, and a self-learning AI engine to optimize routes with minimal human intervention.





Business Challenge



To scale bike-based delivery in dense European cities, the client needed to grow operations without overwhelming dispatch managers.

 Deliveries ranged from fast food (e.g., McDonald's, Burger King) to refrigerated medical packages — each with strict handling requirements.

Manual route planning could only optimize ~20% of deliveries

Dispatchers struggled to manage:

- Diverse delivery conditions
- Varying courier capabilities
- Tight service windows

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Technical Challenge

Route planning had to consider not only geographic distribution but also:



Strict delivery windows:

two-hour slots, morning/evening windows, or ASAP same-day orders.



Item-specific constraints:

refrigeration, fragility, weight, temperature control, and urgency.



Terrain complexity:

routes had to balance uphill/downhill/ flat paths to prevent rider fatigue.



Dynamic order flow:

new deliveries added mid-route required real-time recalculations.

This complexity outpaced basic algorithms, requiring a smarter system that could learn from real operations and continuously adapt.

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Vehicle compatibility:

standard bicycles, e-bikes, and electric tricycles — each with different terrain and load capacity.

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Manager knowledge:

only humans could initially detect impractical combinations (e.g., stacking three uphill stops for a courier with a heavy load and no electric assist).





Model definitions

MODEL NAME	ARCHITECTURE	PROVIDER	PURPOSE	INPUT	Ουτρυτ	USAGE CONTEXT	
RouteAccept-LGBM	LightGBM (Gradient Boosting Decision Trees)	Azure ML	Predicts whether a route will be accepted, the reason for correction, and potential SLA risk	Structured delivery route features (~60 per route)	Classification label + score + ETA deviation estimate	Core dispatch logic, live route filtering	
RouteScore-RNN	GRU-based recurrent neural network	Custom	Evaluates sequential logic and terrain consistency across the delivery path	Ordered stop list with metadata (20–30 steps)	Scoring value + flag for anomalies or fatigue risk	Supplementary scoring layer for complex routes	
FeedbackParse-BERT	Transformer (BERT- style)	Azure ML / Hugging Face	Extracts structured issues from unstructured text comments	Text comments (~512 tokens) from clients, couriers, or dispatchers	Classified labels (e.g. "access problem", "equipment missing")	Post-delivery feedback analysis, route quality loop	
ExplainRoute-GPT	GPT-4 (Generative Transformer)	Azure OpenAl	Generates a natural- language explanation of how and why a route was constructed	Route metadata, constraints, vehicle & item context	Full sentence-level summary of routing logic	Dispatch UI assistant, Al transparency layer	



MODEL NAME	AVG INFERENCE TIME	RETRAINING FREQUE
RouteAccept-LGBM	~300 ms	Weekly
RouteScore-RNN	~400 ms	Monthly
FeedbackParse-BERT	~800 ms	Monthly
ExplainRoute-GPT	~1-1.2 sec	No retraining (prompt-based)

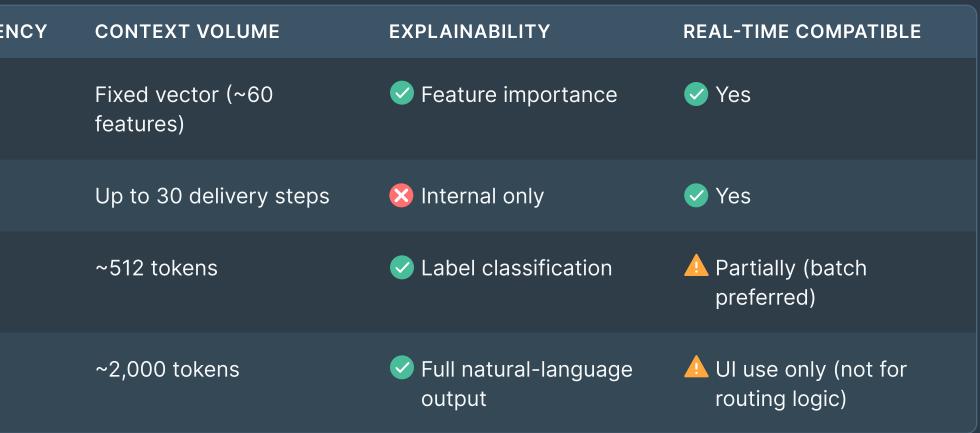


Azure Machine Learning



Google Maps API

Runtime characterictics



Tech Stack



React



.NET



Azure SQL Server



Angular

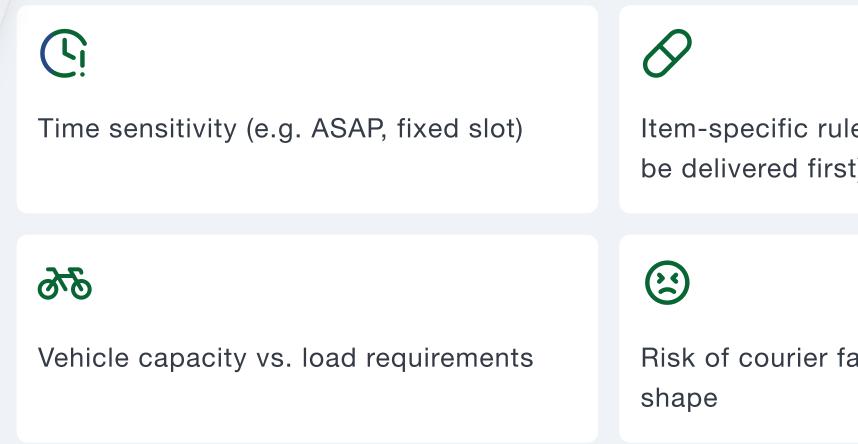


AI Optimization Logic

The AI engine was built as a self-improving assistant for dispatch managers — capable of learning from real-world corrections and continuously improving route quality. The goal was not just to automate routing, but to embed decision-making patterns observed in experienced dispatchers.

Structured Input & Feature Extraction

Each proposed route was transformed into a structured format, breaking down the sequence of delivery points with all relevant



These features were then aggregated to form a high-quality input set used for training machine learning models.

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fatigue based on route	Compatibility between item and vehicle	
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	type (e.g. refrigeration needs)	

Learning from Human Corrections

We analyzed how dispatchers manually edited routes (reordering deliveries, reassigning couriers, removing overloads)

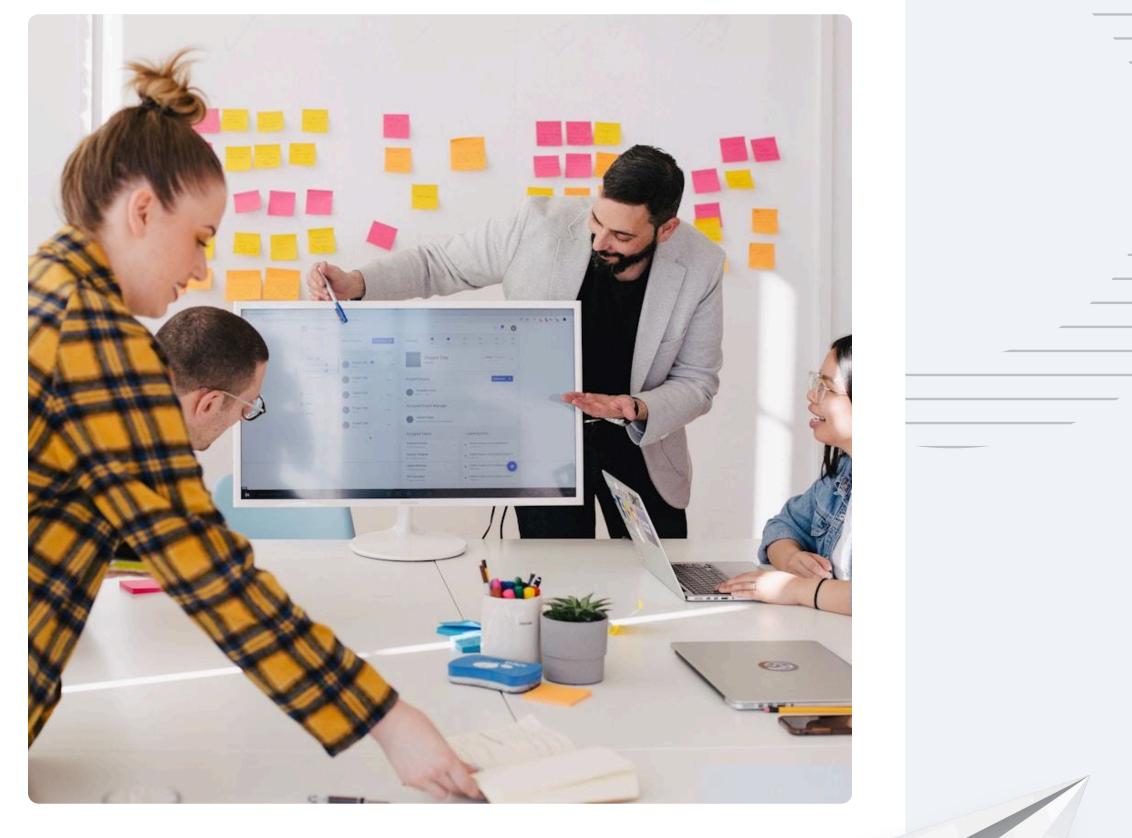
and identified recurring correction patterns.

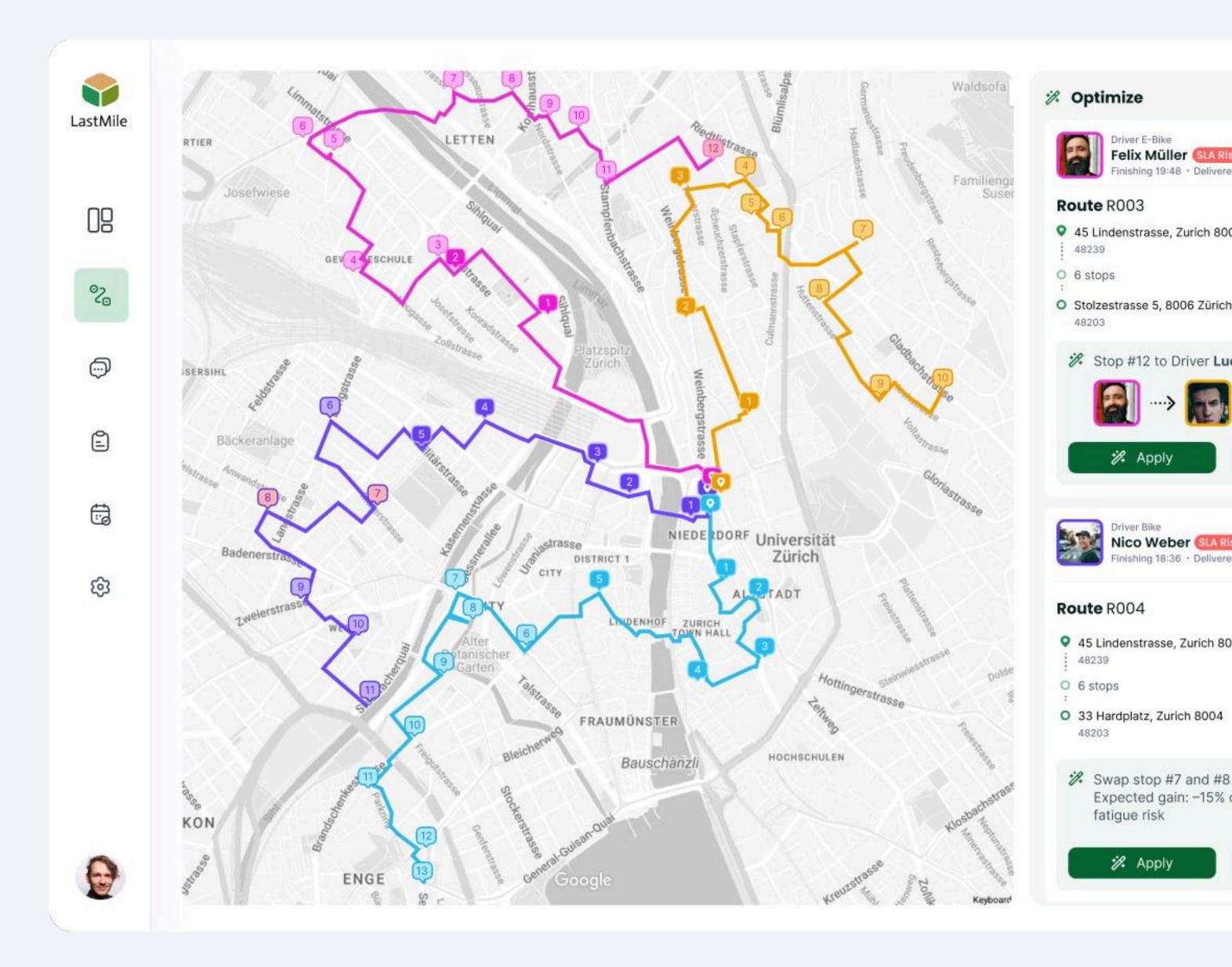
Examples included:

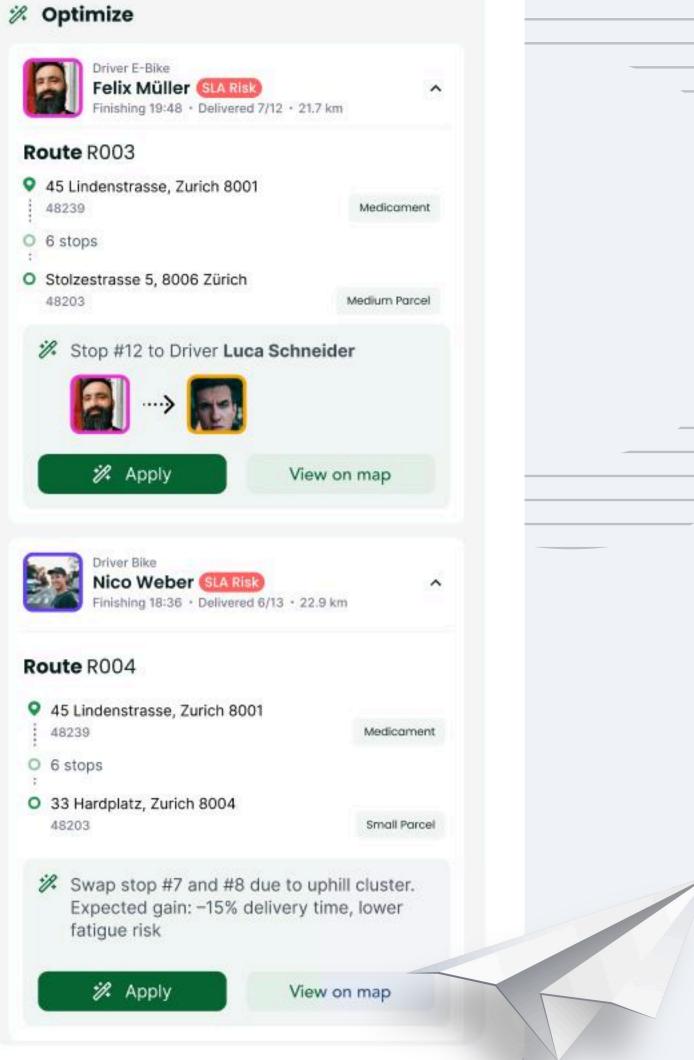
- Medical deliveries placed too late in the sequence
- Too many consecutive uphill stops for non-electric bikes
- Mismatch between parcel size and courier equipment
- Overlapping time slots leading to potential SLA violations ... etc.

This historical decision data allowed us to assign meaning to rejections and create labeled training sets that reflected both acceptance outcomes and the reason behind each correction.

LightGBM was chosen for its speed, accuracy, and explainability — enabling clear reasoning behind AI decisions.







Model Training & Adaptation

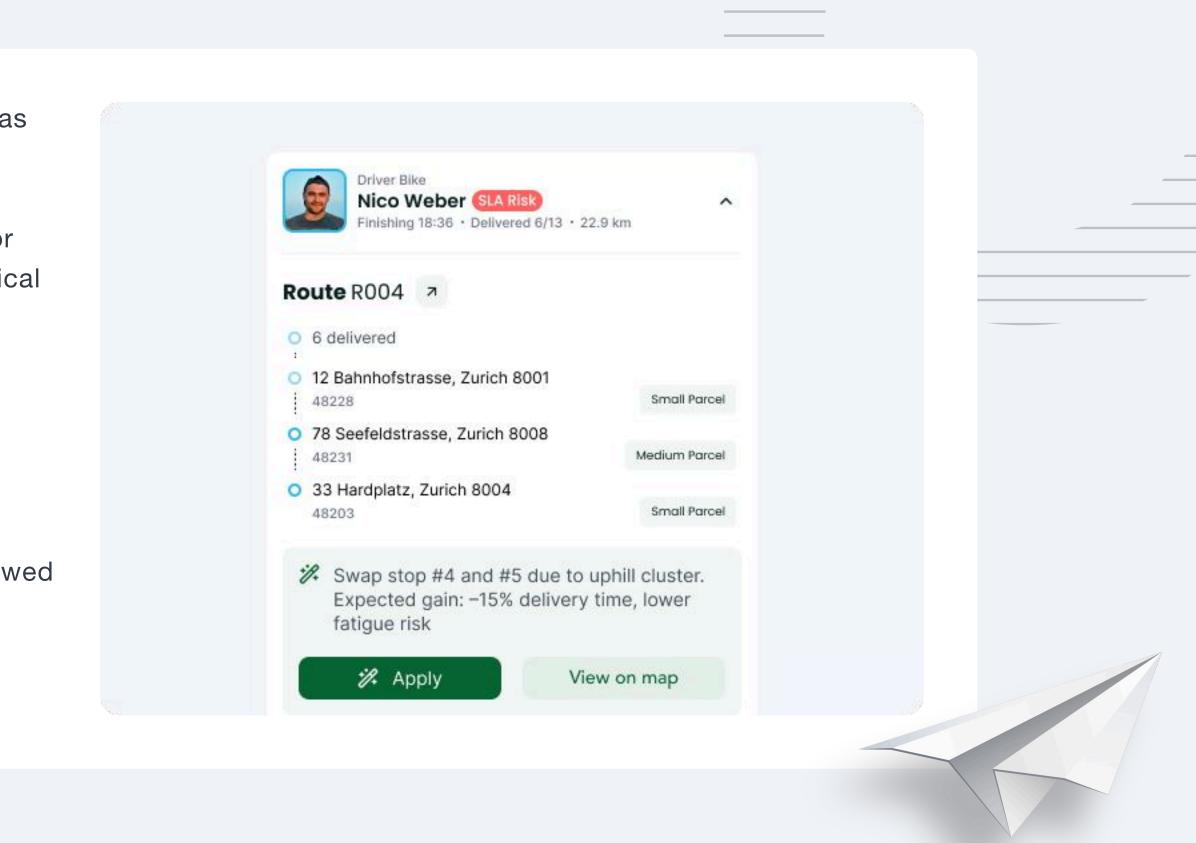
To train our AI models, we used Azure Machine Learning Pipelines — which allowed us to automate the entire flow from raw data extraction to weekly retraining and model evaluation.

We selected LightGBM (Light Gradient Boosting Machine) as the core algorithm for all major tasks. LightGBM is a fast, interpretable, and highly efficient model architecture specifically designed for structured data, making it ideal for learning from delivery routes, vehicle metadata, and historical correction patterns.

The models predicted:

- Whether a route would be accepted or edited
- The likely reason for rejection
- Estimated risk of SLA failure

LightGBM's native support for feature importance also allowed us to visualize the key factors influencing each decision, making AI outputs transparent and easy for dispatchers to trust.



By the second month of use, more than 90% of routes were approved without manual adjustments.

Over time, the assistant became highly reliable – surfacing route suggestions that matched human preferences with minimal need for correction.

Neural Enhancements

To support richer understanding and human-AI collaboration, we added several lightweight neural components:



Route Scoring Assistant,

based on GRU architecture, analyzed routes as delivery sequences to capture hidden inconsistencies missed by flat models.



Feedback Interpretation Model,

(using BERT-style transformer) processed unstructured comments from dispatchers, couriers, and clients to extract insights from real-world events.



Generative Route Explainer,

powered by Azure OpenAl, produced natural language summaries explaining why a route was built in a certain way — improving transparency and trust in Al suggestions.



Our Solution

We delivered a robust enterprise delivery platform with:

Self-learning route engine

Powered by Azure Machine Learning, trained on real dispatch data and dynamic delivery constraints.

Terrain-aware route modeling

Built on Google Maps with elevation and traffic data for precise path planning.

Courier-aware assignment logic

Matches orders to bikes, e-bikes, or tricycles based on capacity, terrain, and load type.

Rich delivery metadata

Supports time windows, item fragility, refrigeration needs, and delivery priorities.

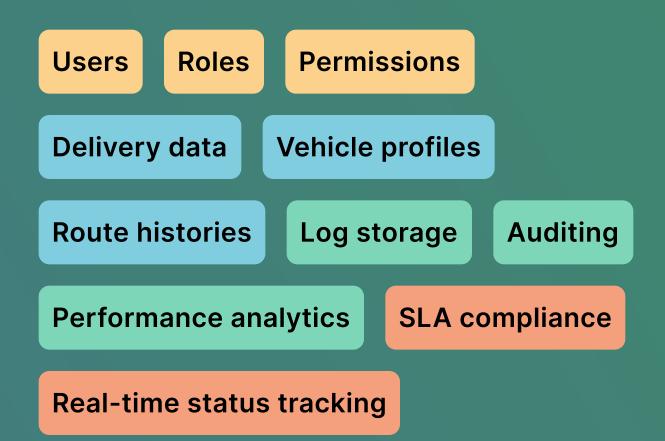
Seamless B2B integrations

Connected to food chains, postal providers, and third-party platforms.

Role-based access control

Tailored workflows for dispatchers, riders, support staff, and clients.

Unified backend on Azure SQL Server managing:



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Impact

98% Al route accuracy

after 2 months of learning from human feedback

85% reduction

in manual dispatch effort

35% drop

in courier fatigue incidents via smarter terrain-aware distribution

42% improvement

in SLA compliance across all delivery types

12+ cities and 5+ enterprise partners onboarded

through fast and scalable deployment

Zero rebuilds required

architecture scaled seamlessly with business growth

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