# Connected Insights: Quantifying the Financial Impact of Supply Chain Timeliness

## BUSINESS PROBLEM

MochoCo, a global retailer with ~$20B in annual supply chain operating costs and hundreds of thousands of seasonal SKUs, faces significant financial losses from supply chain lateness. Late purchase orders (POs) reduce revenue by shortening selling windows and forcing markdowns, yet decisions to expedite shipments via air freight -- accounting for ~1% of products analyzed in this work -- are made without evaluating their net financial impact. Existing KPIs like GIA measure on-time delivery but don't quantify financial consequences, making it impossible to determine whether expediting a given PO improves or destroys profitability.

## DATA SOURCES

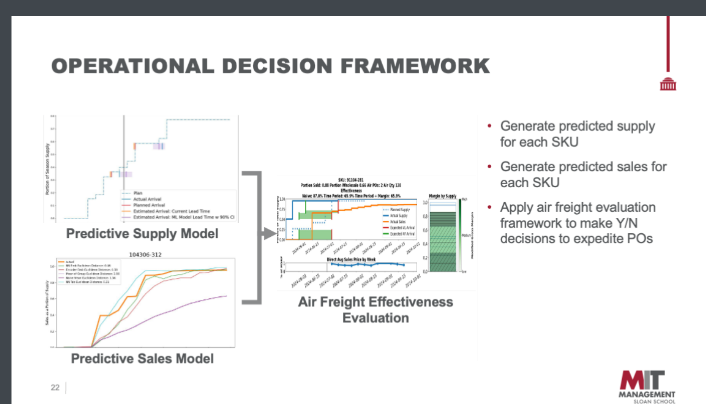
Sales Data Supply Data at the PO Level

Data Types and Format

Boolean, Categorical (nominal), Count (integer), Image, Numeric, Ordered (ordinal), Structured, Text, Time series (Dynamic)

## APPROACH

The work builds a framework that standardizes supply & sales data into cumulative 19-week seasonal curves and develops two predictive models: (1) a lead time model trained on 714K+ PO observations to predict supply arrival; and (2) a deep learning sales trajectory model leveraging proprietary product similarity embeddings to forecast cumulative sales for new SKUs. These outputs feed into a SKU classification matrix (GIA x financial risk) and a PO-level air freight effectiveness framework to evaluate and prioritize expediting decisions based on expected gross margin

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## IMPACT

The framework revealed that MochoCo's historical air freight decisions were broadly unprofitable: the baseline policy of air-freighting POs produced a net gross margin hit of roughly -23% of associated revenue, with only 1.2% of air-freighted POs generating a positive gross margin outcome. Applying the proposed SKU classification methodology improved gross margin by +10.5-12.3% of associated revenue. When driven by predicted model outputs, the framework achieved +23.7% gross margin improvement on the test set, slightly exceeding the actual-data result of +21.7%. The PO-level effectiveness framework, using predicted outputs, cut the gross margin penalty in half -- from -27.5% (baseline) to -14.0% -- by identifying which POs to avoid expediting. The lost sales estimation methodology found that supply chain lateness costs MochoCo an estimated 3.7% of sales in missed revenue opportunity across the analyzed product set, with a strong correlation (r = -0.65) between GIA deterioration and lost revenue. The sales prediction model (embedding-based neural network) achieved an average Euclidean distance of 0.57 versus the naive baseline of 0.97.

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| **DRIVERS** | Spent tens of millions annually on air freight in the US market alone with no systematic way to evaluate whether those decisions improved profitability. Leadership lacked tools to connect supply chain timeliness to financial outcomes, leaving managers to act on intuition rather than expected gross margin impact -- creating significant risk of value destruction. |
| **BARRIERS** | Key challenges included massive product scale (hundreds of thousands of SKUs), demand uncertainty for new products with no sales history, revenue variability across wholesale vs. direct channels, and supply arrival and sales occurring across time. |
| **ENABLERS** | Proprietary product similarity embeddings (756-dimension vectors developed for online search) were a critical enabler, significantly improving sales trajectory predictions. Internal PO-level supply and demand data spanning 2023-2025, air freight cost estimates from operations, and leadership engagement in scoping the problem were also essential. |
| **ACTIONS** | I standardized supply and sales data into cumulative 19-week seasonal curves, then built effectiveness metrics to label historic air freight decisions. Then developed and benchmarked two predictive models -- a lead time model & an embedding-based deep learning sales trajectory model. These outputs were fed into a SKU classification matrix and PO-level framework to identify profitable expediting opportunities & estimate lost revenue from lateness. |
| **INNOVATION** | 3 novel contributions: (1) a time-horizon-based framework translating supply lateness into SKU and PO-level gross margin impact, accounting for seasonal demand decay and mixed wholesale/direct revenue; (2) use of contrastive learning encoders on product similarity embeddings for new-SKU sales trajectory forecasting (3) a lost-sales estimation method that manipulates lateness inputs to isolate revenue lost specifically due to supply delays. |
| **IMPROVEMENT** | The proposed SKU classification framework improved gross margin by +10.5-12.3% of associated revenue versus a -23% baseline. The PO-level effectiveness approach cut the gross margin penalty from -27.5% to -14.0%. The embedding-based sales model reduced prediction error by ~41%. Lost sales opportunity due to lateness was quantified at 3.7% of revenue. |
| **BEST PRACTICES** | Standardizing supply and sales into cumulative time-series curves enables consistent comparison across thousands of SKUs. Similarity embeddings outperform tabular features for new-product forecasting. Decision frameworks should optimize for cost avoidance, not just revenue capture -- most value came from stopping unnecessary air freight. |
| **OTHER APPLICATIONS** | The framework generalizes to any supply chain prioritization action beyond air freight -- manufacturing schedule changes, consolidator prioritization, or DC bypass routing. It is also applicable to other seasonal, new-product retailers facing similar wholesale/direct channel complexity. |