



**Faculty of Gina Cody School of Engineering &
Computer Science**

**Department of Institute for Information System
Engineering**

Procurement Intelligence & KPI Dashboard with Predictive Analytics

by

Manan Paghdar

Problem & System Overview	2
1 . Problem Context	2
2 . Project Objective	2
3 . System Overview	3
4 . Key Assumptions	4
Model & Baseline Analytics Results	5
1 . Analytical Approach	5
2 . KPI Definitions & Feature Engineering	5

3 . Baseline Descriptive Results	6
Predictive & Scenario Analysis Results	7
1 . Supplier Risk Prediction Model	7
2 . Price Forecasting Analysis	10
3. What-If Scenario Analysis	11
4. Observations	12
Business Insights & Decision Support	13
1. Automated Insights & Interpretability	13
2 . Managerial Implications	14
Conclusion	15

Problem & System Overview

1 . Problem Context

Procurement functions play a critical role in controlling organizational costs, ensuring supply continuity, and maintaining supplier quality. However, many procurement teams rely on fragmented spreadsheets or static business intelligence dashboards that provide only retrospective visibility into past transactions.

Such approaches make it difficult to assess supplier performance holistically, identify emerging risks, or evaluate the downstream impact of procurement decisions. Issues such as delayed deliveries, quality defects, non-compliant purchasing, and price volatility are often identified only after they have already disrupted operations.

Additionally, traditional procurement reporting focuses primarily on descriptive metrics and lacks predictive capabilities. As a result, decision-makers are unable to proactively identify high-risk suppliers, anticipate cost fluctuations, or evaluate alternative sourcing strategies under changing performance requirements.

To address these challenges, a unified procurement intelligence system that integrates descriptive analytics, predictive modeling, and scenario-based decision support is required.

2. Project Objective

The objectives of this project are to:

- Develop an end-to-end procurement intelligence system using historical purchase-order data

- Quantify supplier performance using standardized KPIs such as lead time, defect rate, compliance, and negotiated savings
- Identify potentially risky suppliers using machine learning–based classification
- Forecast price trends at the category level to support strategic sourcing decisions
- Enable scenario-based “what-if” analysis to assess the impact of stricter performance requirements

The focus of this project is on **decision support**, rather than isolated metric optimization, reflecting real-world procurement analytics practice.

3 . System Overview

The implemented system represents a simplified but realistic procurement analytics environment:

- Transaction-level purchase order dataset
- Multiple suppliers across multiple item categories
- Historical order and delivery records
- Pricing, quantity, quality, and compliance information

System flow:

Purchase Orders → Data Processing & Feature Engineering → KPI Computation → Predictive Modeling → Decision Support Insights

The system is implemented as an interactive web application using Streamlit, allowing users to explore procurement data dynamically rather than relying on static reports.

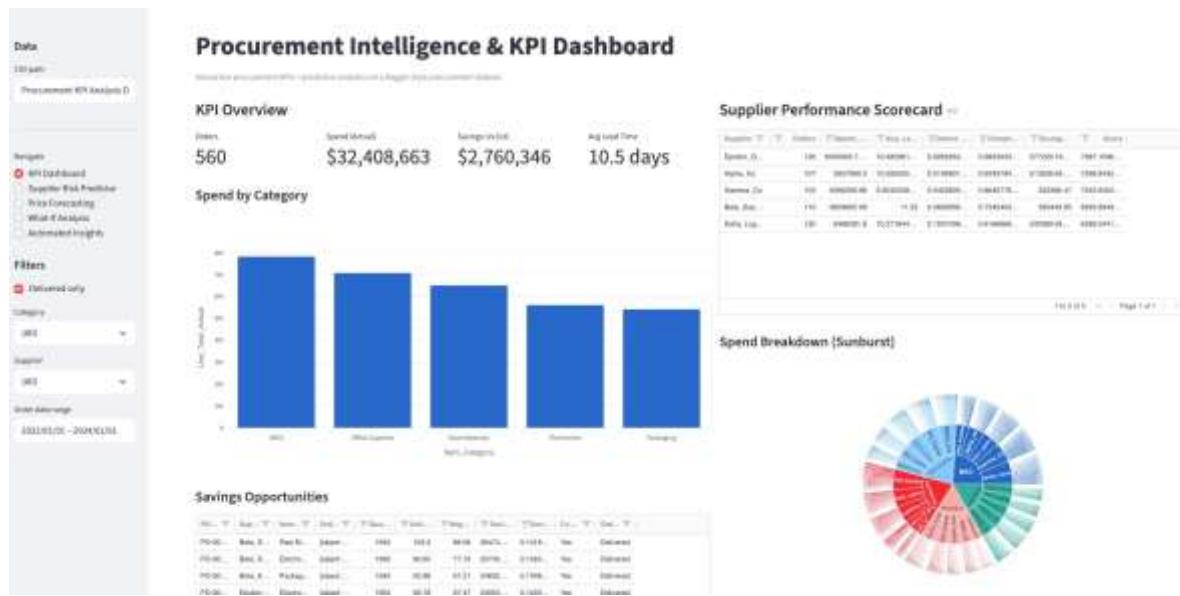


Figure 1. Interactive procurement intelligence system showing KPI dashboard and navigation structure.

4. Key Assumptions

Due to limitations in the available dataset, several assumptions are made:

- Supplier delivery performance is proxied using observed lead times
- On-time delivery is approximated using category-level service thresholds
- Supplier risk is inferred from quality defects, delivery delays, and compliance behavior
- Price trends are analyzed at an aggregated category level

These assumptions enable meaningful analysis while preserving analytical transparency and interpretability.

Model & Baseline Analytics Results

1 . Analytical Approach

The analytical approach adopted in this project follows a structured progression from descriptive analytics to predictive decision support.

First, raw purchase order data is cleaned and transformed into standardized procurement KPIs through feature engineering. These KPIs provide visibility into supplier performance, cost behavior, and operational efficiency. Baseline descriptive analytics are then used to assess the current state of procurement performance without predictive assumptions.

Subsequently, predictive models and scenario-based tools are layered on top of the baseline analytics to support proactive decision-making. This section focuses specifically on the **baseline analytical layer**, which establishes performance benchmarks against which predictive and scenario results are later evaluated.

2. KPI Definitions & Feature Engineering

To convert raw transactional data into actionable procurement intelligence, several key performance indicators (KPIs) were derived.

Lead Time

Lead time is defined as the number of days between purchase order creation and delivery completion:

$$\text{Lead Time (days)} = \text{Delivery Date} - \text{Order Date}$$

Lead time serves as a proxy for supplier delivery performance and is used extensively throughout the analysis.

Defect Rate

Supplier quality performance is captured using defect rate:

$$\text{Defect Rate} = \frac{\text{Defective Units}}{\text{Quantity Ordered}}$$

This metric enables consistent comparison of quality performance across suppliers and categories.

Spend & Cost Savings

Procurement spend and savings are calculated as:

$$\text{List Spend} = \text{Quantity} \times \text{Unit Price}$$

$$\text{Actual Spend} = \text{Quantity} \times \text{Negotiated Price}$$

$$\text{Savings} = (\text{Unit Price} - \text{Negotiated Price}) \times \text{Quantity}$$

These measures quantify the financial impact of supplier negotiations and purchasing decisions.

Compliance Rate

Compliance is treated as a binary indicator reflecting whether a purchase order adheres to internal procurement policies. Supplier-level compliance rates are computed as the proportion of compliant orders.

Supplier Performance Scorecard

Supplier	Orders	Spend_Actual	Avg_Lead_Time	Defect_Rate	Compliance_Rate	Savings_Totals	Score
Epsilon_Group	120	6939305.7700000005	10.485981308411215	0.0262962...	0.983333333333...	577220.16999...	7987.109670376984
Alpha_Inc	107	5957060.3	10.59550561977528	0.0195601...	0.934579439252...	613928.64999...	7586.849563440408
Gamma_Co	103	6366208.96	9.903225806451612	0.0452805...	0.864077669902...	552366.47	7540.840037640608
Beta_Supplies	110	6659805.99	11.23	0.0820056...	0.754545454545...	583440.95	6935.894994368229
Delta_Logistics	120	6486281.8	10.271844660194175	0.1037438...	0.616666666666...	533389.95999...	6398.04415658246

1 to 5 of 5 | < < Page 1 of 1 > >

Figure 2. Supplier performance scorecard summarizing delivery, quality, compliance, and savings KPIs.

3. Baseline Descriptive Results

Baseline descriptive analytics provide a snapshot of procurement performance across suppliers and categories.

At the aggregate level, the dataset reveals substantial variation in supplier lead times, defect rates, and compliance behavior. While some suppliers consistently deliver on time with minimal defects, others exhibit longer lead times, higher quality issues, or frequent policy non-compliance.

Supplier performance scorecards aggregate these KPIs to provide a comparative view of supplier reliability and value contribution. In parallel, spend and savings analysis highlights areas of cost concentration and identifies purchase orders with the highest realized savings.

These baseline results establish a reference point for evaluating supplier risk, forecasting price trends, and assessing the impact of stricter performance requirements in subsequent analyses.

KPI Overview

Orders	Spend [Actual]	Savings [vs list]	Avg Lead Time
560	\$32,408,663	\$2,760,346	10.5 days

Spend by Category

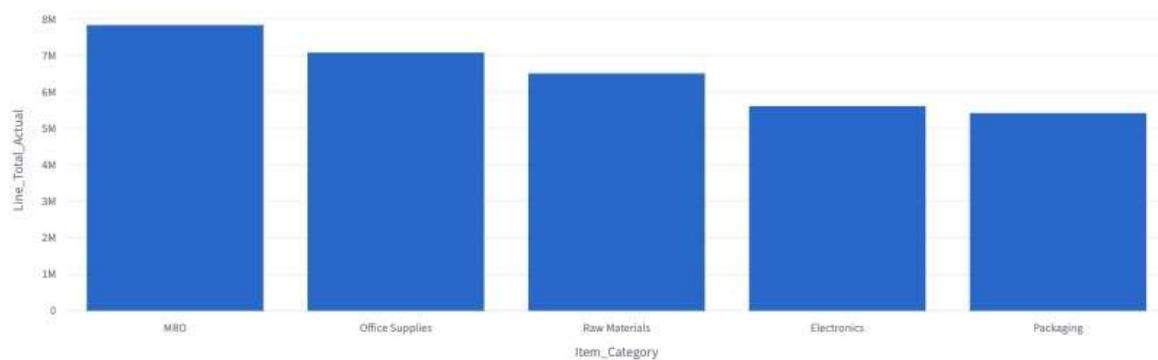


Figure 3. Baseline procurement KPIs and spend distribution across item categories.

Savings Opportunities

PO_ID	Supplier	Item_Cat...	Order_Date	Quantity	Unit_Price	Negotiated...	Savings_T...	Savings_Pct	Compliance	Order_Status
PO-00169	Beta_Supplies	Raw Materials	2023-10-03	1945	103.2	88.56	28474.800000...	0.1418604651...	Yes	Delivered
PO-00122	Beta_Supplies	Electronics	2023-07-06	1995	90.65	77.75	26795.500000...	0.1423055708...	Yes	Delivered
PO-00737	Beta_Supplies	Packaging	2022-12-25	1942	93.98	81.31	24605.140000...	0.1348159182...	Yes	Delivered
PO-00763	Epsilon_Group	Electronics	2022-04-28	1954	99.78	87.47	24053.740000...	0.1293714171...	Yes	Delivered
PO-00011	Epsilon_Group	Raw Materials	2022-03-31	5000	78.49	73.68	24049.999999...	0.0612816919...	Yes	Delivered
PO-00777	Beta_Supplies	Office Supplies	2023-12-09	1988	105.2	93.23	23796.359999...	0.1137832699...	Yes	Delivered
PO-00361	Alpha_Inc	Raw Materials	2023-11-19	1725	92.14	79.62	23321.899999...	0.1451578269...	Yes	Delivered
PO-00253	Gamma_Co	Raw Materials	2023-04-24	1765	97.51	84.3	23315.650000...	0.1354732847...	Yes	Delivered

1 to 8 of 20 < < Page 1 of 3 > >

Figure 4. Purchase orders ranked by negotiated cost savings, highlighting high-impact procurement opportunities

Predictive & Scenario Analysis Results

1 . Supplier Risk Prediction Model

Model Motivation

While baseline KPIs provide valuable historical insights, procurement decisions often require **forward-looking risk identification**. Suppliers that exhibit poor delivery reliability, quality issues, or non-compliance may pose operational risks even if past performance appears acceptable on average.

To address this need, a supervised machine learning model was developed to classify purchase orders as **potentially at-risk**, enabling proactive supplier monitoring.

Risk Definition & Labeling Strategy

Because the dataset does not include an explicit supplier risk label, a **proxy risk definition** was constructed based on operational performance indicators. A purchase order is classified as *at-risk* if at least one of the following conditions is met:

- Defect rate exceeds 5%
- Compliance flag is “No”
- Lead time exceeds the supplier-specific 75th percentile

This rule-based labeling strategy reflects realistic procurement risk heuristics while maintaining interpretability.

Model Architecture

A Random Forest classifier was selected due to its robustness on tabular data and its ability to capture non-linear relationships between features.

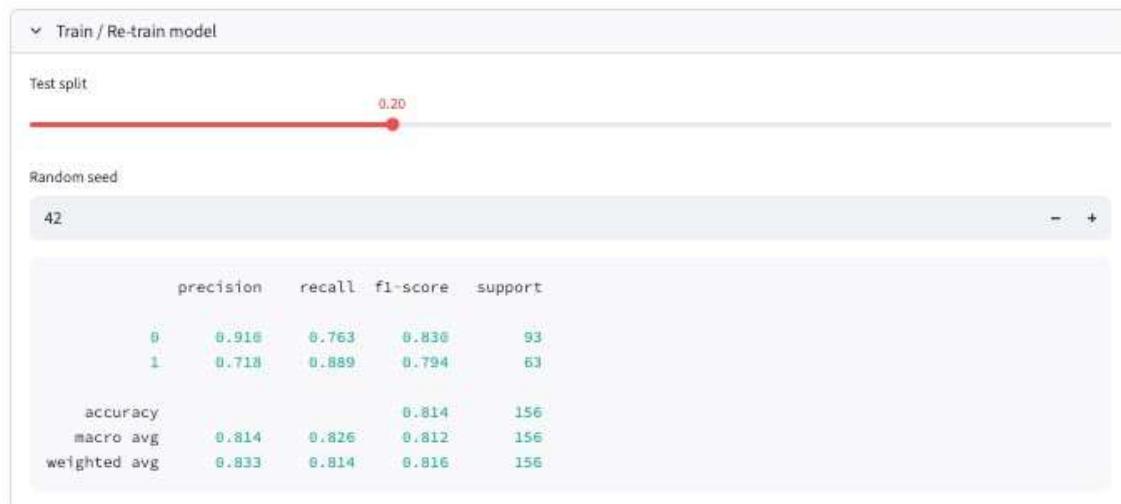
Model inputs include:

- Item category
- Order quantity
- Unit and negotiated prices
- Lead time
- Defect rate
- Compliance indicator
- Savings percentage

The model outputs a **risk probability score** for each purchase order, enabling ranking and prioritization of supplier risk.

Supplier Risk Predictor (Random Forest)

This model flags at-risk orders (proxy for supplier risk) using engineered signals: lead time, defect rate, compliance, and savings volatility.



Predict risk for filtered data

P...	S...	O...	D...	I...	Q...	Q...	U...	N...	D...	C...	L...	D...	L...	S...	S...	R...	R...		
PO...	Bal...	16/...	30/...	MRO	Del...	690	22.47	21.94	77	Yes	14	0.1...	15...	15...	0.5...	39...	0.0...	0.9...	1
PO...	Del...	23/...	09/...	MRO	Del...	1677	22.98	21.71	246	Yes	17	0.1...	38...	36...	1.2...	21...	0.0...	0.96	1
PO...	Ga...	16/...	02/...	Ele...	Del...	778	64.17	61.8	47	Yes	17	0.0...	49...	47...	2.6...	19...	0.0...	0.9...	1
PO...	Del...	06/...	NaT	Pa...	Del...	1578	48.33	42.77	206	Yes		0.1...	76...	87...	5.6...	87...	0.1...	0.95	1
PO...	Bal...	27/...	11/...	Ra...	Del...	1775	47.82	45.86	180	Yes	15	0.1...	84...	81...	1.9...	34...	0.0...	0.9...	1
PO...	Del...	29/...	06/...	Ele...	Del...	1648	95.42	91.46	0	No	8	0	58...	51...	3.9...	65...	0.1...	0.9...	1
PO...	Ga...	02/...	18/...	Ra...	Del...	1045	47.88	44.65	69	Yes	16	0.0...	50...	46...	3.2...	33...	0.0...	0.94	1
PO...	Del...	28/...	13/...	Ra...	Del...	979	51.58	49.69	148	Yes	16	0.1...	50...	48...	1.9...	18...	0.0...	0.94	1
PO...	Del...	15/...	16/...	Ele...	Del...	203	23.14	20	0	No	1	0	46...	4060	3.1...	63...	0.1...	0.9...	1
PO...	Del...	13/...	17/...	Offi...	Del...	1396	94.76	84.06	210	Yes	4	0.1...	10...	117...	10...	14...	0.1...	0.9...	1

Tip: Use filters on the left to narrow to a supplier/category and see the highest risk rows.

Figure 5. Machine learning-based supplier risk predictions ranked by estimated risk probability.

Key Insight

The risk prediction model reveals that supplier risk is driven by combinations of delivery delays, quality defects, and compliance failures rather than any single factor in isolation. This highlights the importance of multi-dimensional performance evaluation over reliance on individual KPIs.

2 . Price Forecasting Analysis

Forecasting Motivation

Procurement cost management is strongly influenced by price volatility across item categories. Relying solely on historical averages limits the ability to anticipate future cost pressures and negotiate contracts proactively.

To support strategic sourcing decisions, category-level price forecasting was implemented using historical unit price data.

Forecasting Methodology

Unit prices were aggregated on a monthly basis for each item category. Time-series forecasting was then applied using a probabilistic forecasting framework (Prophet), with a fallback seasonal baseline model when necessary.

The forecasting output provides an estimate of expected future prices over a configurable forecast horizon.

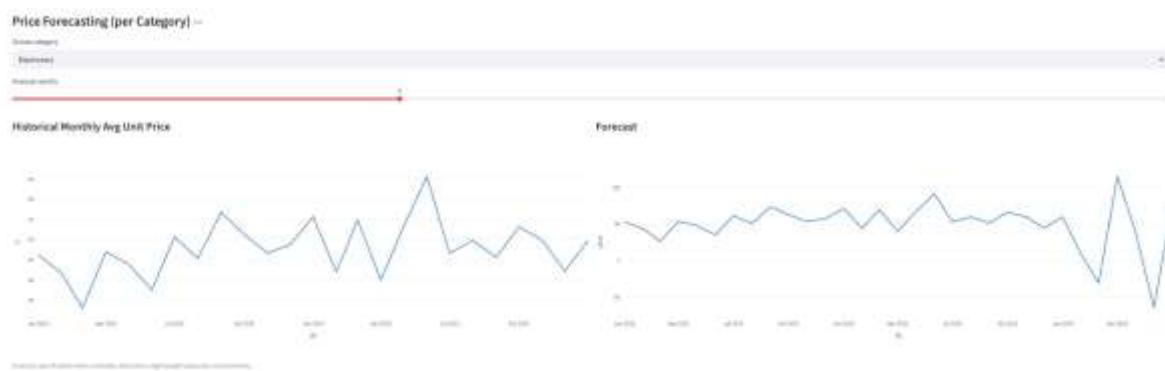


Figure 6. Historical and forecasted unit prices for a representative procurement category.

Key Insight

Price forecasts reveal category-specific trends and volatility patterns that are not visible from historical averages alone. These insights can inform contract timing, forward-buying strategies, and budget planning.

3 . What-If Scenario Analysis

Scenario Design

Beyond predictive modeling, procurement decision-making often involves evaluating trade-offs between cost, service level, and supplier flexibility. To support this process, a scenario-based “what-if” analysis tool was developed.

Due to the absence of explicit promised delivery dates, on-time delivery (OTD) performance is approximated using a lead-time-based service threshold defined at the category level.

Scenario Parameters

The scenario tool allows users to vary:

- Target on-time delivery requirement (e.g., 95%)
- Service-level threshold strictness (lead-time quantile)

Supplier performance is re-evaluated under these constraints to assess portfolio-level impacts.

What-If Analysis (OTD proxy)

Because the dataset has no promised date, we use a lead-time SLA proxy: an order is considered on-time if lead time \leq SLA (default = 75th percentile lead time per category).



Suppliers to review (below target)

Supplier	Orders	OTD	Spend	Savings	Avg_Lead	Defect	Compliance
Beta_Supplies	100	0.72	\$088787.63	\$40992.22	11.23	0.0840963059575...	0.76
Epsilon_Group	107	0.7476635514018...	\$334035.03	\$05960.87999999999	10.485981308411...	0.0281249559316...	0.9813084112149...
Delta_Logistics	103	0.7768990291262...	\$723560.76	\$457678.87999999...	10.271844660194...	0.1017273792912...	0.6116504854368...
Alpha_Inv	89	0.797752808988764	\$955432.61	\$386290.72	10.595505617977...	0.0169443879246...	0.9325842696629...
Gamma_Co	93	0.8602150537634...	\$916038.75	\$503083.58	9.903225806451612	0.0449939908943...	0.8494623655913...

1 to 5 of 5 | < > Page 1 of 1

Figure 7. Scenario-based evaluation of supplier performance under stricter on-time delivery targets.

4 . Observations

- Increasing delivery performance requirements reduces the feasible supplier pool
- Stricter service targets highlight suppliers that may require renegotiation or replacement
- Scenario-based evaluation enables transparent trade-off analysis between service reliability and cost efficiency

Key Insight

Supplier performance requirements that appear reasonable under historical analysis can significantly reshape the supplier portfolio when evaluated under stricter service constraints. Scenario-based tools are therefore essential for robust procurement decision-making.

Business Insights & Decision Support

1 . Automated Insights & Interpretability

While dashboards and predictive models provide powerful analytical capabilities, procurement decision-makers often require **clear, interpretable summaries** rather than raw metrics or model outputs. To address this need, an automated insights generator was incorporated into the system.

The insights module synthesizes KPI trends, supplier performance statistics, and model outputs into concise, plain-language observations. These insights are designed to highlight operational risks, negotiation opportunities, and potential policy violations without requiring users to manually inspect multiple dashboards.

Examples of generated insights include:

- Identification of suppliers exhibiting unusually high defect rates, suggesting the need for quality audits
- Detection of low-compliance suppliers, indicating potential contract enforcement issues
- Recognition of categories with concentrated savings opportunities, guiding negotiation prioritization
- Highlighting suppliers with excessive lead times, prompting safety stock or sourcing adjustments

This approach bridges the gap between analytical outputs and managerial interpretation, increasing the usability of the system for non-technical stakeholders.

Automated Insights Generator

Rule-based insights + simple NLP phrasing. Use filters on the left to focus on a supplier or category.

1. Supplier Delta_Logistics has a high average defect rate (10.4%). Consider a quality audit or tighter incoming inspection.
2. Supplier Delta_Logistics shows low compliance (62% 'Yes'). Consider enforcing contract terms or switching to compliant suppliers.
3. Supplier Beta_Supplies has the longest average lead time (11.2 days). Consider safety stock, earlier ordering, or alternate suppliers.
4. Category MRO contributes the most negotiated savings (\$672,428). Prioritize negotiation playbooks here.
5. Review orders with high savings but low compliance: they may represent policy exceptions or maverick buying.

Evidence snapshot

PO_ID	Supplier	Item_Categ...	Order_Date	Delivery_D...	Lead_Time...	Defect_Rate	Compliance	Savings_To...
PO-00211	Gamma_Co	Office Supplies	01/01/2024 00:00	NaT		0.0527169506...	Yes	12345.6789000...
PO-00520	Delta_Logistics	Raw Materials	27/12/2023 00:00	28/12/2023 00:00	1	0.1000000000...	Yes	4750.4799999...
PO-00238	Epsilon_Group	MRO	26/12/2023 00:00	04/01/2024 00:00	9	0.0342820181...	Yes	9490.6000000...
PO-00684	Alpha_Inc	Electronics	25/12/2023 00:00	12/01/2024 00:00	18	0.0219399538...	Yes	1160.4399999...
PO-00429	Beta_Supplies	Raw Materials	24/12/2023 00:00	NaT		0.1003584229...	No	284.58000000...
PO-00386	Beta_Supplies	Packaging	22/12/2023 00:00	11/01/2024 00:00	20	0.0000000000...	No	469.65000000...
PO-00082	Beta_Supplies	MRO	20/12/2023 00:00	26/12/2023 00:00	6	0.0000000000...	Yes	4862.9999999...
PO-00472	Gamma_Co	MRO	20/12/2023 00:00	09/01/2024 00:00	20	0.0588737201...	Yes	2637

1 to 8 of 15 Page 1 of 2

Figure 8. Automatically generated procurement insights derived from supplier KPIs and predictive analysis.

Key Insight

Automated narrative insights significantly reduce the cognitive burden on procurement managers by translating complex analytics into actionable recommendations, thereby improving decision speed and consistency.

2. Managerial Implications

The integrated procurement intelligence system developed in this project supports decision-making at multiple organizational levels.

At the **operational level**, supplier scorecards and savings tables enable buyers to:

- Monitor delivery and quality performance
- Identify high-impact cost-saving opportunities
- Detect non-compliant purchasing behavior

At the **tactical level**, supplier risk predictions and scenario analysis help procurement managers:

- Proactively identify suppliers requiring intervention
- Evaluate the impact of stricter service-level requirements
- Prioritize supplier development or replacement strategies

At the **strategic level**, price forecasting and aggregated spend analysis support:

- Long-term sourcing and contract negotiations
- Budget planning under price volatility
- Risk-aware supplier portfolio design

By integrating descriptive analytics, predictive modeling, and scenario-based evaluation within a single interactive system, the solution moves beyond static reporting and enables data-driven procurement governance.

Key Insight

The value of procurement analytics is maximized when insights are embedded directly into decision workflows rather than delivered as disconnected reports. This system demonstrates how analytics can function as an operational decision-support tool rather than a retrospective reporting artifact.

Conclusion

This project demonstrates how procurement data can be transformed into an integrated decision-support system through the combination of descriptive analytics, predictive modeling, and scenario-based evaluation.

Starting from raw purchase-order data, standardized procurement KPIs were derived to quantify supplier performance, cost behavior, and compliance. Baseline analytics revealed substantial heterogeneity across suppliers and categories, highlighting the limitations of relying on historical averages or isolated metrics. These findings motivated the development of predictive and scenario-driven analytical layers.

A machine learning–based supplier risk model was implemented to proactively identify potentially problematic suppliers using interpretable proxy risk definitions grounded in operational performance indicators. In parallel, category-level price forecasting provided forward-looking insights to support strategic sourcing and budget planning. A what-if scenario analysis tool further enabled transparent evaluation of trade-offs between delivery performance requirements, supplier availability, and cost implications.

To bridge the gap between analytics and managerial action, an automated insights module translated complex analytical outputs into concise, plain-language recommendations. Together, these components position the system as an operational procurement intelligence platform rather than a static reporting exercise.