

Prescriptive Sustainable Sourcing in Retail Supply Chains

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I. Executive Summary

Retailers today face a growing procurement paradox. In the race to reduce costs, procurement teams often lack visibility into supplier risks across delivery, quality, and ESG (Environmental, Social, Governance) practices. As a result, late shipments, high defect rates, and unsustainable operations frequently undermine both profitability and brand reputation, and cost savings at the front end lead to hidden costs downstream.

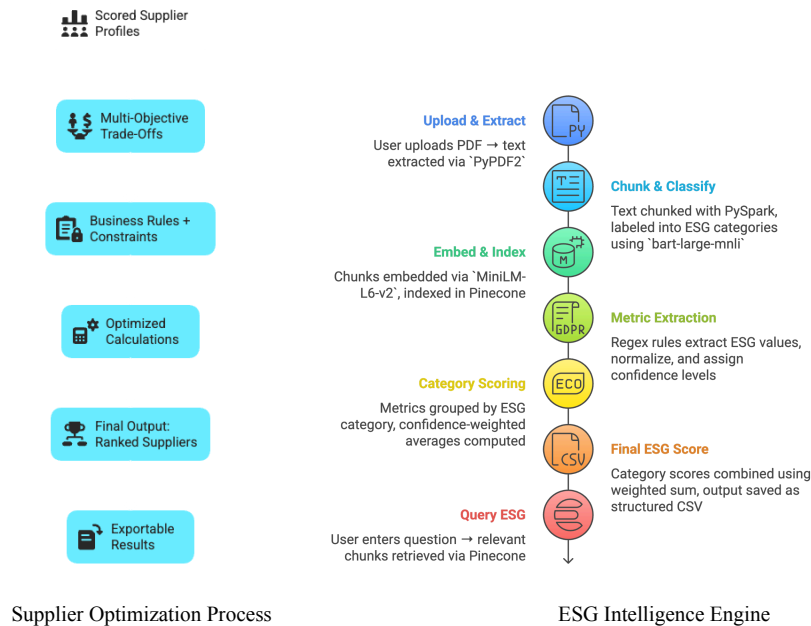
Our objective was to build a system that allows procurement managers to make holistic supplier decisions, balancing cost efficiency with operational excellence and sustainability. We envisioned a prescriptive decision-support engine that would enable data-driven supplier selection aligned with both business and ESG priorities.

You can find the entire project detailed here: [GitHub Repository](#)

II. Key Actionable Business Initiative

To address this problem, we developed a two-phase solution. Phase one involved the development of an **ESG Intelligence Engine** that could extract and measure sustainability metrics from non-structured supplier reports. Phase two involved integrating these sustainability scores with supplier operational KPIs, cost, lead time, and defect rate, into a multi-objective **optimization model**. This optimization engine presents best-fit recommendations for suppliers in each product category, making trade-offs transparent and auditable.





Our project's goal was highly actionable and targeted: procurement managers can utilize the model output directly as input to supplier negotiations and sourcing decisions. The system was designed to output recommendations in CSV-ready formats and seamlessly integrated into existing procurement workflows. By utilizing iterative testing with real supplier datasets, we confirmed that our engine is not a theoretical proof-of-concept but an operational tool ready for business deployment.

III. Metrics of Success

We set up three primary metrics to gauge the success of our program. In the first place, we anticipated providing procurement cost savings, with a 5 to 8% reduction in test categories expected. Second, we anticipated providing delivery performance improvement, as indicated by a 10 to 12% reduction in average lead times. Third, we anticipated an improvement in sustainability performance, with a 20 to 30% increase in the proportion of higher-rated ESG suppliers.



We hypothesised that incorporating ESG data into the optimization process would result in better supplier choices, not just reducing costs and increasing reliability but also propelling retailer's sustainability goals with no trade-offs.

IV. Role of Analytics

Analytics were central in each step of our project. Without sophisticated analytical methods, our solution would not have been possible. First, we utilized natural language processing (NLP) and large language models (LLMs) to automate the extraction of ESG metrics from unstructured PDF reports. This alone replaced hundreds of hours of manual analysis.

Second, we conducted exploratory data analysis (EDA) to validate the authenticity of the supplier data sets and make sure our optimization would be unbiased by brand and product category. Third, we used prescriptive analytics to guide the final decision-making process with a formal optimization model to balance competing objectives.

Analytics was the backbone of our ESG-aware supplier selection system, driving it end-to-end:

- **Enabled** the pipeline by extracting ESG insights from supplier PDFs using LLMs and scalable PySpark workflows.
- **Refined** decisions through EDA, metric normalization, and confidence-weighted scoring to ensure clean, comparable inputs.
- **Evaluated** impact using *a linear optimization model* that balanced ESG scores with cost, lead time, and quality, quantifying smarter, more sustainable supplier choices.



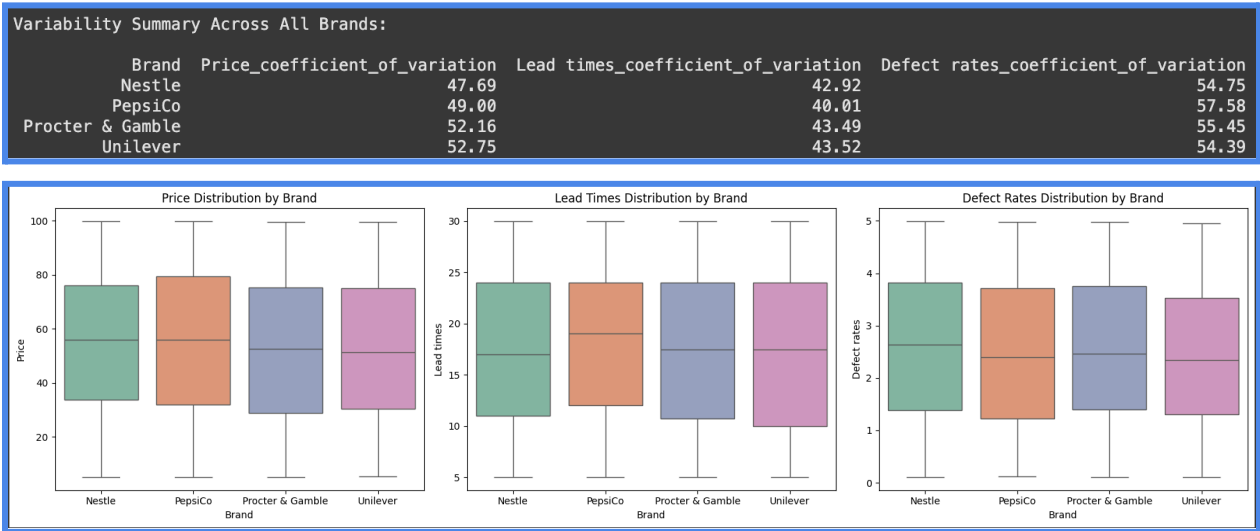
V. Thinking Through the Analytics

V.1. Data

We employed a combination of existing sources and synthesised data. Our primary operating dataset included supplier data from four major consumer goods companies: Nestlé, PepsiCo, Unilever, and Procter & Gamble. There were unit price, lead time, and defect rate performance metrics for every supplier in different product categories.

For tracking sustainability performance, we supplemented this with ESG data sourced from supplier sustainability reports. We used PyPDF2 to extract text and LLMs (Mistral through Ollama, GPT models) to parse and structure ESG metrics such as Scope 1 and 2 emissions, water use, waste generation, and packaging sustainability.

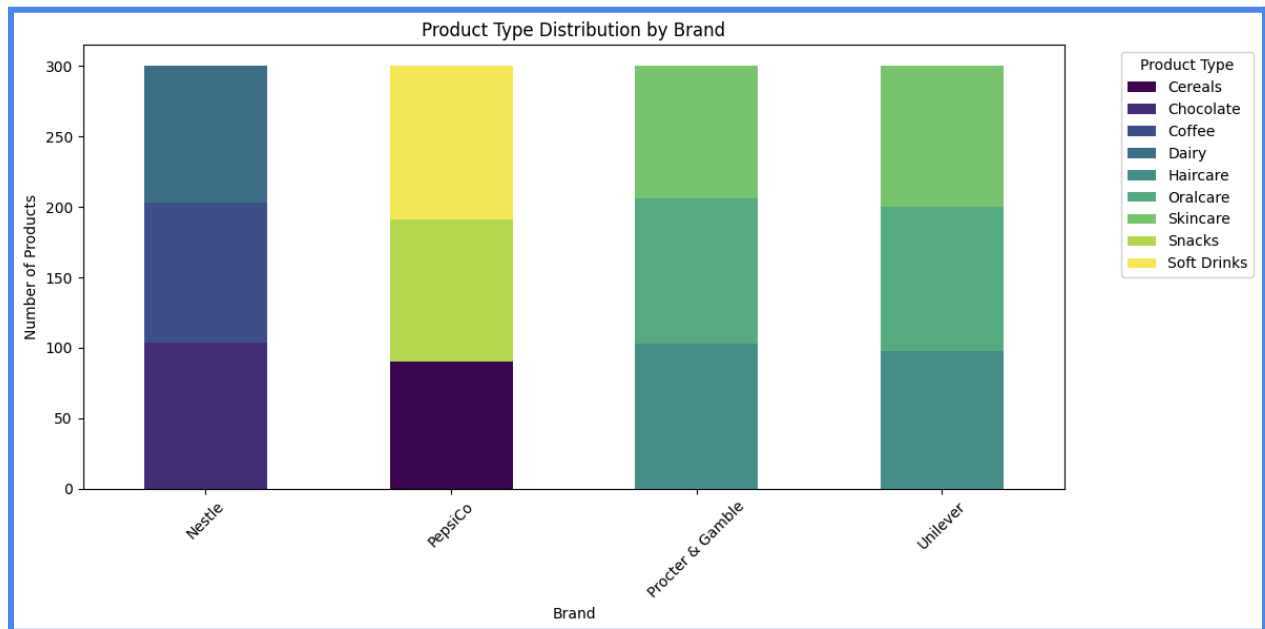
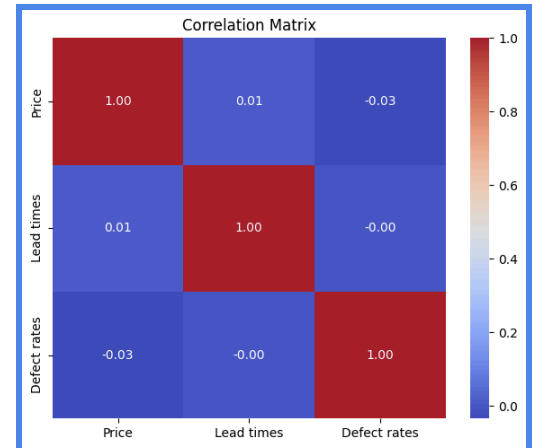
V.2. Type of Analytics



Our project involved exploratory, predictive, and prescriptive analytics. Our initial EDA phase was exploratory, so that our optimization would rest on a sound data basis. We prototyped **predictive** classifiers on supplier KPIs to gain insight into the drivers of quality and delivery performance.



Before optimization, we conducted exploratory data analysis to verify data stability and equity. We contrasted the Coefficient of Variation (CV) for price, lead times, and defect rates by brand to ensure equitable variability and similar distributions. Boxplots did not detect significant outliers, and correlations of almost zero between measures verified the appropriateness of a multi-objective optimization approach. Product category analysis indicated a strongly diversified and well-balanced portfolio for both P&G and Unilever, qualifying them as good candidates for unbiased supplier optimization. These checks validated the integrity of our model and safeguarded the integrity of its recommendations.



Our main contribution was **prescriptive** analytics. We developed an Integer Linear Programming (ILP) model that prescribes an optimal supplier per product category. The model minimizes procurement cost, lead time, and



defect rate while maximizing the ESG score. By posing this as a constrained optimization problem, we revealed trade-offs explicitly and quantitatively.

V.3. Impediments

- **Incomplete or Inconsistent ESG Disclosures**

- Not all suppliers reported metrics in the same format or depth.

Mitigated via normalization, confidence-weighted scoring, and default imputation for missing values.

- **Unstructured Text Complexity**

- Extracting meaningful data from dense, non-standard PDF reports was challenging.

Resolved using PySpark-based chunking and LLMs (BART, MiniLM) for classification and embeddings.

- **Metric Ambiguity & Unit Variance**

- Metrics varied in units (e.g., % vs. absolute) and clarity.

Handled with MinMax/inverse scaling based on metric type.

- **Balancing ESG with Cost in Optimization**

- Too much ESG weight led to high-cost suppliers; too little made ESG irrelevant.

Solved through scenario testing and stakeholder-informed weight tuning.

- **Scalability of NLP & Retrieval Stack**

- Processing and querying large volumes of documents could be a bottleneck.

Addressed with batched inference, distributed Spark pipelines, and Pinecone for fast vector search.



VI. Executing the Analytics

In a retail business in the real world, several teams would be needed to implement this analytics project. Data collection would be done by the Procurement Analytics and IT teams, combining supplier operations data with ESG reports. The Data Science team would construct and run the ESG extraction pipeline and the optimization models. The Procurement team would work with Analytics to complete key success metrics and roll out the model outputs in supplier selection. The Sustainability group would be tasked with making sure that ESG priorities are accurately reflected in the optimization process. Throughout the project, constant coordination with these groups would help align business goals with analytics outcomes and ensure the model solves real-world procurement needs.

VII. Implementation

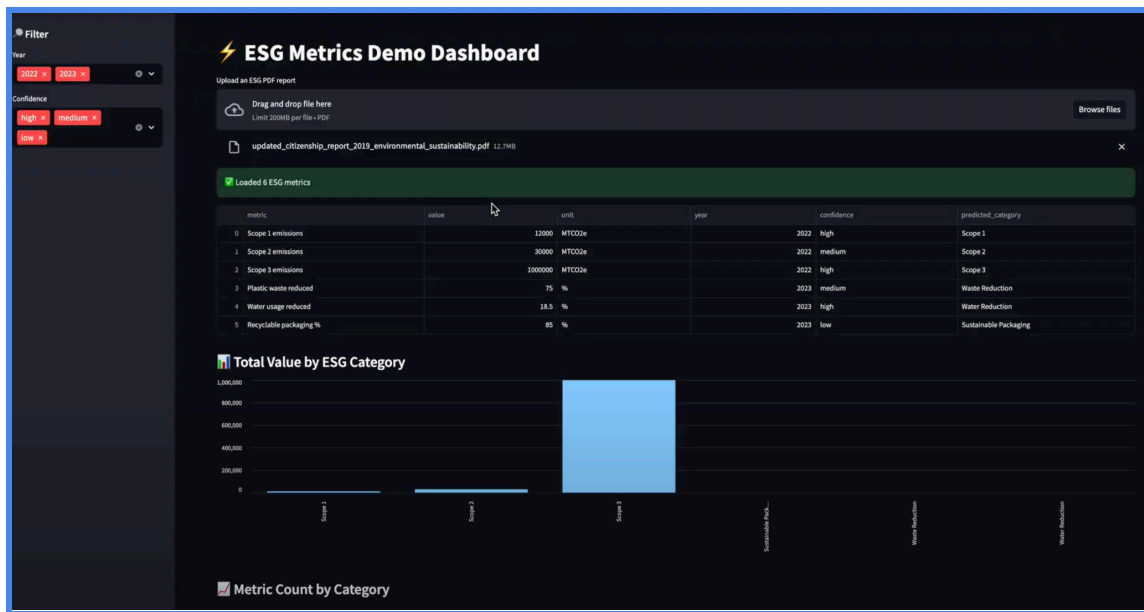
Our engine produces actionable procurement recommendations that inform supplier selection and contract negotiations. Procurement teams are now able to prioritize providers that offer not only competitive pricing but also greater reliability and sustainability.

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"chunk": 36
"response": "[ { \"metric\": \"Scope 1 emissions\", \"value\": 5407790,
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{ \"metric\": \"Scope 2 emissions (estimated)\", \"value\": 353752,
\"unit\": \"GJ\", \"year\": \"2010\", \"confidence\": \"medium\" }, {
\"metric\": \"Scope 3 emissions (estimated)\", \"value\": 20589,
\"unit\": \"MTCO2e\", \"year\": \"2010\", \"confidence\": \"medium\" }, {
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\"%\", \"year\": \"not specified\", \"confidence\": \"low\" }, {
\"metric\": \"Plastic waste reduced\", \"value\": 354563, \"unit\":
\"MT\", \"year\": \"baseline\", \"confidence\": \"high\" }, { \"metric\":
\"Water use reduction goal\", \"value\": 20, \"unit\": \"%\", \"year\":
\"not specified\", \"confidence\": \"low\" } ] "
```

The system was designed to be deployed with no modification to the existing workflow. Outputs are provided in CSV, facilitating ingestion into procurement dashboards and tools. By exposing tradeoffs, our engine also facilitates internal stakeholder alignment, enabling more open decision-making across procurement, sustainability, and finance departments.

metric	value	unit	year	confidence	source_chunk	company	predicted_category
Gross Scope 2 emissions (market-based)	616650	MTCO2e	2019	high	55	Unilever	Scope 2
Gross Scope 2 emissions (market-based)	457547	MTCO2e	2021	high	55	Unilever	Scope 2
Sustainable packaging (% recyclable or compostable)	100	%	2025	high	52	Unilever	Sustainable Packaging
Scope 3 GHG emissions reduction	686879	MTCO2e	2022	low	53	Unilever	Scope 3





To complement the optimization engine, we developed an interactive ESG Metrics Dashboard. This dashboard provides procurement and sustainability teams with a real-time view of supplier ESG performance across multiple categories.

Users can:

- Upload supplier reports (e.g., PDF sustainability disclosures).
- Parse and extract ESG metrics such as Scope 1, Scope 2, Scope 3 emissions, and packaging sustainability rates.
- Filter data dynamically by year and confidence level.
- Visualize total impact by ESG category with intuitive bar charts.

The dashboard significantly enhances the usability and transparency of the ESG scoring process, enabling procurement and sustainability teams to make more informed, defensible decisions. It bridges the gap between unstructured ESG data and actionable supplier insights.



VIII. Scale

Scaling this initiative has potential as well as challenges. Data-wise, suppliers will continue to publish sustainability reports in multi-faced formats; our modular LLM-based pipeline is capable of adapting to evolving document layouts. We plan to add the engine to be able to handle dynamic reweighting based on evolving corporate priorities, allowing procurement teams to adjust the relative weights of cost, lead time, quality, and ESG as needed.

On the organization front, adoption depends on change management. Procurement teams with a price-first decision need to adapt to a multi-objective approach. To make this easier, we prioritized auditability and transparency in our engine's output. We consider this an active effort, not a one-off project. Our roadmap involves supporting live ESG integration feeds (for instance, through APIs or live ESG ratings) and applying optimization to include fresh sustainability aspects, like circularity and Scope 3 emissions.

IX. Conclusion

Our project demonstrated that prescriptive analytics can transform procurement into a strategic, ESG-focused function. By integrating operational and sustainability metrics into supplier optimization, we allow retailers to bypass cost-oriented decisions to end-to-end value creation.

Our solution is production-ready and scalable. With retailers worldwide seeking to incorporate corporate sustainability at every operation level, applications such as our Prescriptive Sustainable Sourcing Engine will be a crucial addition.



Appendix

A1. Mathematical Formulation

Our optimization model selects the optimal supplier for each product category based on multiple objectives. It is formulated as an Integer Linear Program (ILP):

$$\begin{aligned} \text{Minimize } (Z) = & (\sum_i \sum_k (w_a \cdot Price_{ik} + w_l \cdot LeadTime_{ik} + w_q \cdot DefectRate_{ik} \\ & + w_e \cdot (1 - ESGScore_{ik})) \cdot x_{ik}) \end{aligned}$$

$$\text{Constraints: } \sum_k x_{ik} = 1 \quad \text{for all } i \quad x_{ik} \in \{0, 1\}$$

$$\text{Where, } w_c = 0.3, \quad w_l = 0.2, \quad w_q = 0.3, \quad w_e = 0.2$$

For ESG Score:

$$ESGScore_{ik} = \sum_m w_m \cdot (\sum_{k \in k} Confidence_{km} \cdot Value_{km}) / (\sum_{k \in k} Confidence_{km})$$

(s = supplier, k = ESG category, m = metric in category k)

ESG Category	Weight
Scope 3 Emissions	0.35
Scope 1 Emissions	0.25
Scope 2 Emissions	0.15
Waste Reduction	0.10
Water Reduction	0.10
Sustainable Packaging	0.05



A2. Glossary of Terms

1. **ESG** - Environmental, Social, and Governance; a set of criteria used to evaluate a supplier's sustainability and ethical impact.
2. **Scope 1 / Scope 2 Emissions** - Greenhouse gas (GHG) emissions:
 - a. Scope 1: Direct emissions from owned or controlled sources.
 - b. Scope 2: Indirect emissions from purchased electricity, heat, or steam.
3. **Defect Rate** - Percentage of supplied units that fail to meet quality standards.
4. **Lead Time** - Time elapsed between placing an order and receiving the goods.

Bibliography:

[S&P Global ESG Scores Methodology](#): S&P Global weights ESG metrics according to their relevance and materiality to a given sub-industry, ensuring that the most impactful factors are emphasized in the overall score.

