Negotiation Buddy: A Machine Learning–Powered Assistant for Data-Driven Procurement Strategy

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ABSTRACT

Our sponsor seeks to transform negotiation into a data-driven process while preserving institutional knowledge of category sourcing strategies. To support this goal, we developed the *Negotiation Buddy*, an intelligence tool designed to help sourcing professionals identify key negotiation levers and generate effective counteroffers. The tool integrates sourcing practices such as Kraljic's Matrix and Porter's Five Forces into a structured, analytics-driven workflow. Through an intuitive dashboard, users receive tailored recommendations based on internal value, risk assessments, and external market dynamics. Historical rate card data is processed using machine learning to uncover patterns in supplier behavior. We applied K-Means clustering with category-specific features (e.g., supplier, role, and experience level) and historical rates. The analysis revealed an optimal clustering of three groups, each demonstrating distinct pricing and negotiation behavior. To predict supplier pricing, we trained an XGBoost regression model that achieved strong accuracy (MAE = $6.80, MAPE = 9.38%). SHAP analysis clarified the contribution of controllable (e.g., contract terms, timing) and uncontrollable factors (e.g., inflation, labor cost shifts) on pricing. The pilot was conducted within the sponsor's procurement function for application development services in China, using rate cards from 11 suppliers across 45 roles and three experience levels from 2020, 2022, and 2024. The tool includes a predicted rate card to serve as a benchmark and an analytics module that surfaces key supplier insights and category trends. By capturing and learning from negotiation outcomes, the *Negotiation Buddy* facilitates institutional learning and continuous improvement, helping sourcing teams to negotiate more strategically, consistently, and at scale.

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Sandra: On a personal note, I would like to thank my mom and dad for helping me reach MIT—this achievement would not have been possible without them. Without my talented partner, Bernardo, this research would not have been as enriching and sophisticated. It was a pleasure working with you.

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Table of Contents

1. Introduction

Procurement teams manage the acquisition of raw materials, goods, and services to meet production, inventory, and sales needs (Sai et al., 2002). Sourcing professionals are expected to wield a deep understanding of their sourcing category and the optimal levers to deliver the company's business requirements. These insights are maintained as part of the institutional knowledge of seasoned procurement leaders. However, when those individuals move out of a product category or leave the company, that information is lost and no longer accessible (Schnellbächer and Weise, 2020).

While procurement professionals have more resources to advance their decision-making process than ever before, subcategory-specific sourcing levers are often missed by procurement agents. The institutional knowledge that would inform those insights is scattered across internal records, category managers, category plans, and external resources (e.g. market data providers) (Moghadam and Zarandi, 2002).

Negotiation processes are often inefficient due to varying expertise among stakeholders and the complexity of negotiation variables. Each product category has unique leverage opportunities that new procurement professionals may be unaware of (Lee and Ou-Yang, 2009). Without mentor guidance, these professionals risk missing valuable negotiation advantages. In addition, the procurement professional may incorrectly weigh the importance of negotiation terms to the company or fail to maintain non-compromise areas that the sponsor company considers critical (Zijm et al., 2019). These are among the issues that our project sponsor, like many companies, is encountering in their procurement department.

1.1 Motivation

Our sponsor is a pharmaceutical, biotechnology, and medical technologies corporation that seeks to select suppliers that balance cost efficiency and risk reduction. Currently, our sponsor's procurement professionals submit a Request for Proposal (RFP) for their responsible product category and may receive responses from many suppliers. The suppliers' RFP responses provide information on their price structure, delivery and warranty conditions, and product or service specifications. Procurement professionals are expected to understand the overarching business strategies, compile the provided data, negotiate the price and contract terms, and select the final supplier based on established criteria.

During a negotiation, the sponsor's procurement professional needs prompt access to market intelligence, category insights, and negotiation tactics to propose optimal counteroffers. This requires a multi-disciplinary understanding of negotiable and non-negotiable terms from both the buyer's and seller's points of view. While suppliers may value consolidated purchase orders, multi-year contracts, or opportunities to enter new markets, the buyer may prioritize cost efficiency, enhanced service levels, superior product quality, or risk-averse payment terms (Schnellbächer & Weise, 2020; Davis & Vogt, 2021).

1.2 Problem Statement

The company's goal is to improve the quality of their procurement team's negotiating decisions and to accomplish more with their resources. Procurement professionals are often tasked with synthesizing incoming RFP responses, historical pricing data, and category-specific sourcing strategies under significant time constraints with static resources. Undertaking negotiations during the RFP process with a clear understanding of category dynamics and strategic sourcing levers—mechanisms that procurement teams can use to drive cost savings, improve supplier performance, and enhance overall value during the sourcing process— can lead to a more successful outcome (Rotmensen et al., 2023). In our sponsor's organization, procurement professionals are routinely rotated across categories to promote broad-based experience and leadership development. While this approach cultivates versatility, it disrupts the continuity of institutional knowledge within categories. As a result, optimal negotiation opportunities may go unexplored, particularly when less experienced team members lack a deep understanding of category-specific dynamics. The sponsor aims to reduce the variability of procurement success due to team experience, so that they can see more consistent employment of optimal negotiation tactics.

To achieve this goal, the sponsor's procurement professionals must advance their ability to ask the right questions, consider previously hidden points of leverage, and shed light on other visibilities that could assist in negotiation. Improving the outcomes of procurement negotiations should not disrupt the procurement team's efficiency; rather, the procurement professional should feel they are entering negotiations of less familiar product categories with more confidence and support.

The motivations and problems described above culminated in the following questions:

(1) How can the sponsor company enable procurement professionals, regardless of their level of experience, to consistently negotiate with suppliers based on an optimal balance of price and value?

(2) How can the sponsor company standardize the identification and weighting of key negotiation terms to ensure consistently advantageous outcomes?

Our sponsor's procurement team aims to bring more data-driven precision into the complex process of negotiation and to retain the institutional knowledge of category sourcing levers. In doing so, the sponsor company seeks to capture cost savings and cost avoidance by reducing the cost of goods as well as the cycle time to complete the sourcing activity.

1.3 Project Goals and Expected Outcomes

The primary goal of this project is to design and develop a model that will support our sponsor company's procurement team in managing requests for proposals (RFPs) and ensuring strategic execution throughout the negotiation process, particularly in the IT category.

The sponsor company envisions the creation of an intelligence tool, named the Negotiation Buddy, to arm their procurement team with previously unobtainable insights during the negotiation process. The sponsor's users could interact with the tool, providing input that informs the tool of the sourcing event at hand. The tool would then synthesize a variety of external and internal resources to identify key negotiation areas and generate effective counteroffers. The Negotiation Buddy should support the negotiation process, rather than serve as an autonomous tool. Additionally, the sponsor company values a robust feedback loop to improve the accuracy and relevancy of its output over time.

Companies are increasingly seeking ways to improve negotiation outcomes by leveraging advanced data analysis tools. Technologies such as K-Means clustering can deliver accurate classifications of the supplier's bidding behavior when evaluating supplier proposals, helping to uncover untapped value during negotiations. Machine learning (ML) further enhances long-term value by preserving institutional knowledge, which can support sourcing agents in decision-making, especially those new to a product category (Brown, 2021).

The Negotiation Buddy model uses a machine learning model (i.e. XGBoost) to predict rate cards offers specific to each supplier as well as category-specific sourcing tactical levers to guide procurement teams in strategic negotiations. It evaluates supplier offers, recommends a negotiation protocol for the RFP, and enhances price transparency through benchmarking and vendor cost analysis.

Collaboration with our sponsor and its suppliers is key to project success. Procurement stakeholders will be engaged early in the process to contribute to the model's design and parameter tuning, ensuring alignment with the sponsor's business strategy. The model's recommendations will then be measured by comparing its decisions to historical RFP outcomes. Input from subject matter experts and stakeholders involved in these negotiations will further refine the model. Success will be measured through reduced spend and improved procurement efficiency, as demonstrated by shorter negotiation cycles, increased consistency in supplier selection aligned with strategic objectives, and optimized allocation of procurement resources. Additionally, the tool's effectiveness will be validated by its ability to minimize deviations between initial negotiation targets and final contractual outcomes. This holistic approach ensures measurable improvement in cost savings, reinforced strategic alignment across procurement teams, and preservation of institutional knowledge.

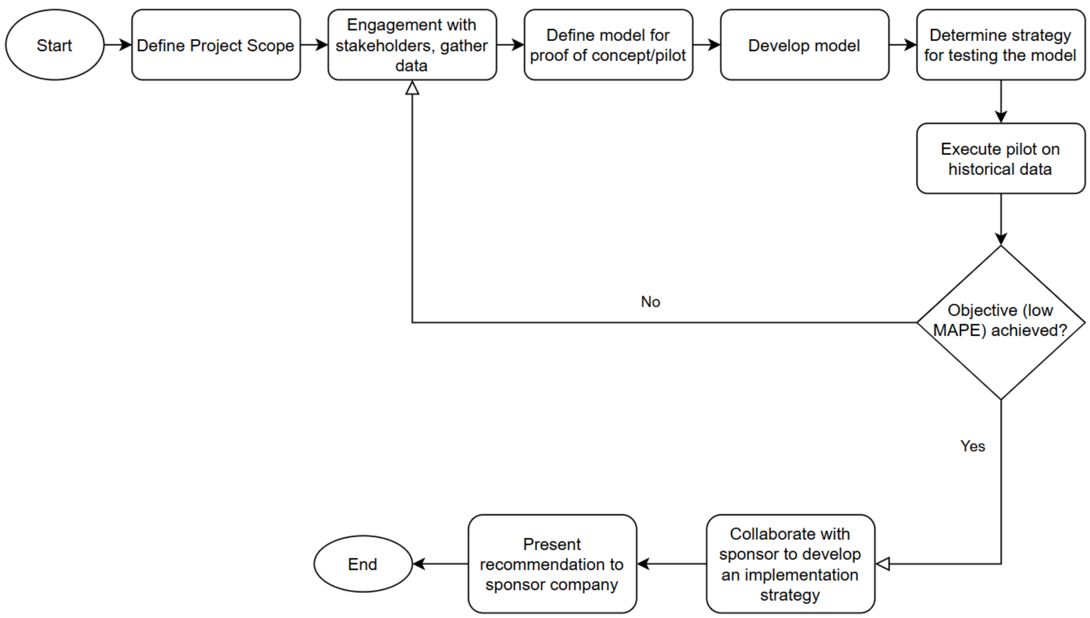
To bring the Negotiation Buddy from concept to implementation, we followed a structured project plan that guided our collaboration with the sponsor, data analysis, model development, and final deployment strategy. This plan outlines the sequential steps taken throughout the project to design, validate, and refine the tool.

Plan of Work to develop the Negotiation Buddy:

- Initial Engagement: Collaborate with the sponsor company's procurement team to gather historical data, map the sourcing process, understand the category sourcing strategy, and identify key value drivers.
- Model Development: Create a model by transforming historical RFP data into features aligned with category strategies and key value drivers. Leverage supervised learning to predict negotiation outcomes and clustering to identify supplier segments. Continuously refine the model based on sponsor feedback and performance evaluation.
- Model Performance Evaluation: Analyze the predictive model's outcomes. If results are unsatisfactory, we will refine the model's logic and adjust parameters in collaboration with the sponsor. If results are favorable, we will proceed to the implementation phase.

- Implementation Strategy: Develop a detailed plan to integrate the framework into the sponsor's sourcing process, including stakeholder engagement and adoption strategies.
- Final Recommendation: Present a comprehensive recommendation based on the proof of concept and the proposed implementation strategy.

Figure 1. Plan of Work to develop the Negotiation Buddy



2. State of the Practice

In strategic negotiation, success relies on a nuanced understanding of sourcing dynamics. Best-in-class procurement frameworks provide guidance that can help a professional through the complexity, therefore, they should inform the outputs of a negotiation tool. Such frameworks will train the tool to identify appropriate procurement techniques and to craft negotiation strategies specific to the User's sourcing activity. On the other hand, emerging technologies present the opportunity to systematize such these frameworks, data analysis, and process. To explore both aspects, we examined existing procurement frameworks and the adoption of automation tools in procurement. Our research synthesizes insights across six key areas: category management, supplier segmentation, market analysis frameworks, sourcing levers, negotiation techniques, and automation technology.

2.1 The Evolution of Category Management

Category management is the use of strategic practices for groups of similar goods and services to optimize purchasing decisions, identify best suppliers, and negotiate better terms (North Carolina State University, 2024). Category management helps procurement teams develop lower-level methodologies, such as negotiation playbooks, according to their understanding of their niche product division.

Prior to the 1980s, procurement was handled with impartiality across product types, with the focus on general cost control. The shortcomings of traditional purchasing departments prompted a shift towards strategies that better mitigate risk and align with business strategy (Schiele, 2023). Schiele attributed the growth of category management and the decline of unstructured purchasing to three factors:

i. The inability of procurement professionals to exploit expertise in any one industry when they were responsible for products across multiple industries.
ii. The inability of procurement professionals to leverage deep relationships and insider information when managing too many suppliers.
iii. The increase of purchasing power through bundling, or consolidating purchases across departments, locations, or categories to negotiate better terms with suppliers.

After major disruptions to supply chains in the 1980s, including the oil crisis, the emergence of supplier segmentation frameworks led to further developments in category management.

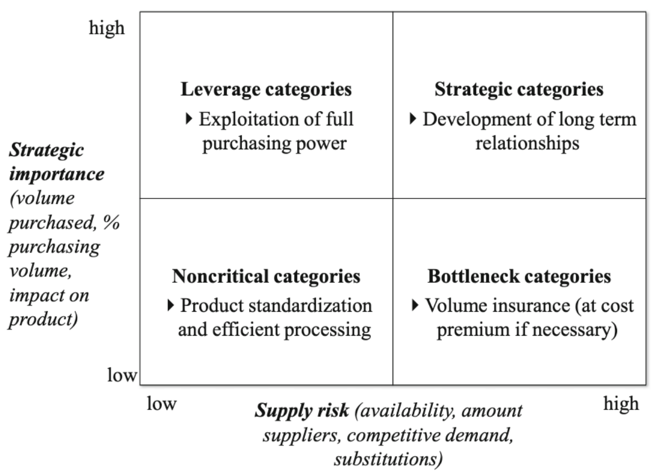
2.2 Supplier Segmentation Frameworks

While category management aligns strategy with an item's characteristics, supplier segmentation offers a structured approach to classify and manage the suppliers of those goods.

Kraljic's Purchasing Portfolio Matrix

Purchasing portfolio models, notably Peter Kraljic's Purchasing Portfolio Matrix in 1983, proposed that supplier segmentation techniques could inform buyers of unique leverage opportunities for different suppliers (Lajimi and Majidi, 2021). As shown in Figure 2, Kraljic categorized suppliers based on two key dimensions: profit impact and supply risk. This segmentation would place suppliers in one of four quadrants in the "Kraljic matrix": Leverage, Noncritical, Bottleneck, and Strategic. Each quadrant was paired with optimal purchasing levers. For the first time, Kraljic's portfolio concept offered "pragmatic advice on how top management can recognize the extent of its own supply weakness and treat it with a comprehensive strategy to manage supply" (Kraljič, 1983). For leverage purchases, the framework proposed the exploitation of purchasing power due to the low risk of changing suppliers. For strategic purchases, it recommended the development of long-term supplier relationships and contingencies plans so as not to disrupt the supply of critical goods. Noncritical purchases were of low strategic importance, so it recommended streamlined processing, and bottleneck purchases were best assisted by tactics like volume insurance and close supplier monitoring (Hesping and Schiele, 2016).

Figure 2. Kraljic's Purchasing Portfolio Matrix (Schiele, 2009)



To use the Kraljic's framework on a specific negotiation event, the procurement professional would classify the strategic importance of the category to the business and analyze its supply risk in the current market. These two descriptions would place the category in one of the four quadrants (Zijm et al., 2019). Once a supplier was selected to engage in negotiations, the procurement professional would better understand the power balance between the supplier and the purchasing team. They would understand which opportunities should be exploited with greater leverage or be left untouched. Additionally, they could use the framework to assist in supplier selection, since the values expressed in the purchasing strategies overlapped with desirable supplier attributes (Schiele, 2019).

Alternative Supplier Segmentation Methods

Supplier segmentation was subsequently adapted into newer portfolio models. An alternative framework was published by Nellore and Doerquist in 2000 to establish a relationship between product categories and supplier types in the automotive industry. Companies have also adopted their own segmentation practices using classifications of category, spend behavior, and geography. For example, Coca-Cola segmented their 13,200-parent-level supplier organization into indirect and direct spend suppliers, and then further into categories of “group critical,” “country strategic,” and “tactical” (Coca-Cola HBC, n.d.). While newer supplier segmentation frameworks have been published, the Kraljic’s approach remains the dominant framework because of its robust application capabilities and simplicity.

2.3 Market Analysis Frameworks

Companies can also use market analysis frameworks to inform negotiation strategies. Among these, Porter's Five Forces model is a commonly used tool that enables procurement teams to decode market dynamics and understand the underlying drivers of profitability within a particular category (Porter, 2008).

Porter's Five Forces framework analyzes five critical dimensions (see Figure 3):

(1) Competitive Rivalry: The intensity of competition among existing vendors

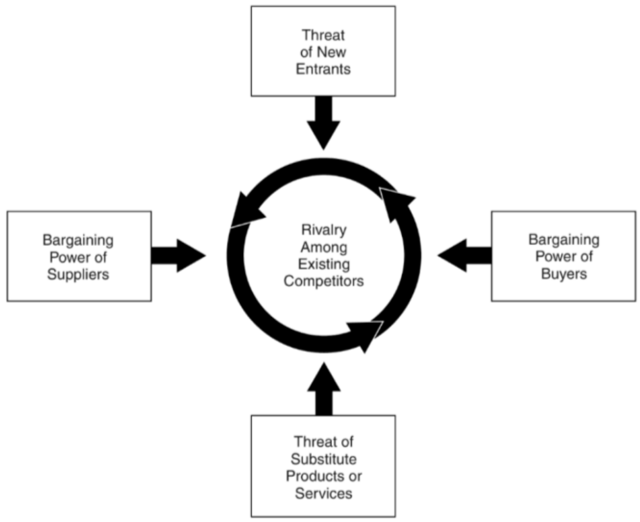
(2) Threat of New Entrants: Potential for new suppliers to disrupt established relationships

(3) Supplier Power: The leverage suppliers possess in dictating terms and prices

(4) Buyer Power: The negotiating strength procurement teams can exert

(5) Threat of Substitutes: The availability of alternative products or services

Figure 3. Porter's "Five Forces that Shape Industry Competition" (Porter, 2008)

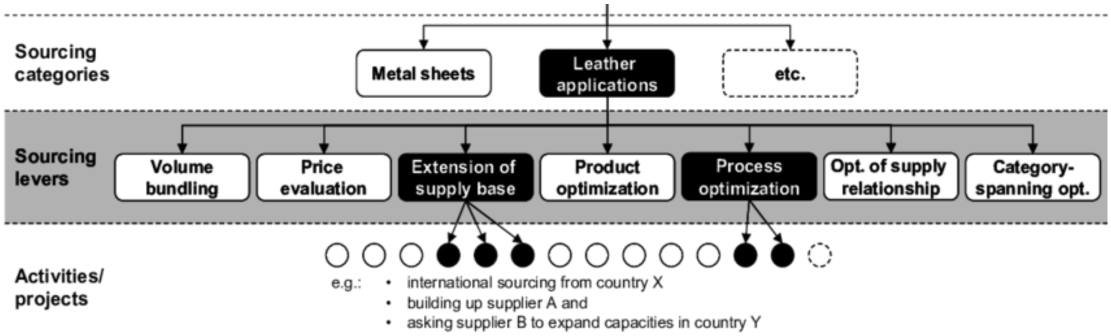


This multidimensional approach transcends superficial market understanding by incorporating considerations such as market maturity, concentration ratios, and relationship dynamics within niche vendor ecosystems (Porter, 2008). By mapping these forces, category managers gain critical insights into power distribution within specific markets. This intelligence enables them identify potential points of vulnerability in their supply chains, recognize opportunities where specific negotiation levers will yield maximum impact, and calibrate their approach based on actual market leverage rather than assumed positioning

2.4 Strategic Sourcing Levers

Category management, supplier segmentation models, and market analysis frameworks all help identify the sourcing levers that are most available and effective in negotiations. There are different methods that categorize the multitude of sourcing lever options (O'Brien, 2012, Cox, 2014). The most vigorous models were synthesized by Hesping and Schiele (2016). Their research proposed that most sourcing levers could be classified into seven categories (see Figure 4): volume bundling, price evaluation, extension of supply base, product optimization, process optimization, optimization of supply relationships, and category-spanned optimization.

Figure 4. Seven Sourcing Levers Framework (Hesping and Schiele, 2016)



2.5 Negotiation in Procurement

Negotiation is the process in which "different parties seek to reach a mutual agreement about an issue, in case of a supplier negotiation about the terms and conditions of a purchasing contract." (Zijm et al., 2019). It considers multi-dimensional elements beyond price; otherwise, it would be relegated to a bargaining exercise. In procurement negotiations, the buyer and seller seek to find alignment despite hidden and often competing interests. Therefore, it is critical for procurement agents to define internal and external purchasing expectations. It is a common practice for agents to define their Least Acceptable Agreement (LAA), Most Desired Outcome (MDO), and Best Alternative to No Agreement (BATNA) (Zijm et al., 2019).

Negotiations in the Seven Step Strategic Sourcing Process

While sourcing goals, strategies, and rules differ between categories, most sourcing activities follow a common process. This process is outlined in the Seven Step Strategic Sourcing Process and includes: defining the spend category, conducting market research, creating a sourcing strategy, soliciting bids, selecting a vendor and negotiation terms, executing the contract, and tracking results (All Things Supply Chain, 2022). Within this sourcing process, a multitude of events can include the act of negotiation. Reverse auctions, proofs of concept, and benchmarking exercises are common activities, however, the most relevant to negotiation is Requests for Proposal. During a Request for Proposal (RFP), suppliers are invited to submit a detailed bid in response to an outline of the expected deliverables and scope of work. After obtaining bids from a pool of suppliers, the procurement team evaluates the bids and selects the best supplier (Rotmensen et al., 2023). Prior to the final supplier selection, the procurement professional may select a shortlist of suppliers to engage in extensive negotiations with.

Nuances in Procurement Negotiations

Negotiation requires a holistic understanding of business goals and supplier relationships. In practice, purchasing agents can use a mix of negotiation levers across various models and quadrants, breaking the "rules" of the recommended tactics. For example, a sourcing team may utilize sourcing levers outside of the prescribed purchasing category if they have a long-term aim to move from a current, difficult procurement position to a future, more leveraged position. In such cases, the Kraljic's Matrix, as well as other supplier segmentation frameworks, are more useful as an idea-generating tool, rather than a rigid prescriber of recommendations (Lajimi and Majidi, 2021). Research by Hesping and Schiele (2016) explored the extent to which procurement professionals applied the sourcing levers suggested by purchasing portfolio models. Upon evaluating 107 sourcing projects, they concluded that procurement professionals "cherry picked" sourcing levers across portfolio quadrants (Hesping et al., 2016). Evidently, practitioners act upon factors more complex than any one prescriptive framework.

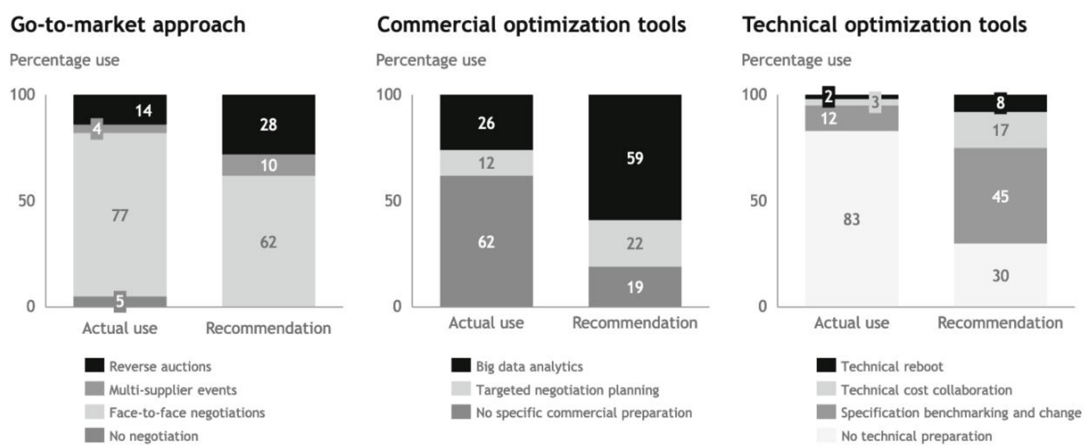
2.6 Automation in Procurement

This section outlines the growing need for advanced digital solutions in procurement, particularly in supplier selection and negotiation. It highlights the challenges posed by inconsistent execution, underutilization of analytical tools, and the lack of negotiation in lower-spend categories, underscoring the case for automation to drive more consistent outcomes.

The Need for Advanced Digital Solutions

Supplier selection negotiation can generate substantial cost savings and positive procurement outcomes. It requires the understanding of the interplay of dynamic and complex variables. Consequently, there is extensive literature on the lost opportunities in negotiation and the reasons for those oversights. One study proposed that negotiation outcomes were largely dependent on the experience of the participating individual(s) (Zijm et al., 2019). Lee and Ou-Yang (2009) suggested that intelligent assistance was necessary to consistently achieve positive outcomes in negotiations in those conditions. On the other hand, it seems that existing procurement frameworks are underutilized. In Schnellbächer and Weise's investigation of fifteen procurement teams, existing price transparency tools, should-cost models, and linear performance pricing tools were used only 15% of the time (Schnellbächer and Weise 2020) (see Figure 5). Finally, the time-consuming process of negotiation is altogether omitted for tail-spend or low-spend categories, leaving any chance of improved outcomes outside the standard terms unobtainable. According to Hoek et al. (2022), around 20% of Walmart's suppliers were contracted with non-negotiated terms.

Figure 5. Comparison of Actual and Recommended Use of Available Tools in Negotiation (Schnellbächer and Weise, 2020)



The digitization of procurement offers a solution to these inefficiencies. The term "Procurement 4.0" was introduced by Bienhaus and Haddud (2018) to describe this new age of procurement driven by data and digital solutions.

The Adoption of Automation Tools

In Procurement 4.0, advanced automation tools enable buyers to apply the "full procurement toolkit", leaving fewer stones unturned during a negotiation. The engine behind these tools is generative artificial intelligence— a specialized branch of AI that produces responses that mimic human thought processes. According to a survey by Foundry and GEP, 65% of senior technology decision-makers believe AI tools have the potential to significantly enhance human decision-making within procurement. Such tools can integrate into supplier selection, contract management, information retrieval, and other key procurement processes (GEP, 2024).

An example of an advanced procurement tool is artificial intelligence-powered “chatbots”, which engages users through a text-based interface. These chatbots can assist procurement professionals in daily sourcing tasks, including data visualization and prescriptive analytics. A pilot project by the MIT Center for Transportation and Logistics sought to develop a chatbot capable of “placing a data scientist in the pockets of every procurement professional”, making underutilized data more accessible. While the research team noted challenges to full-scale implementation, such as security and data access issues, they highlighted the technology’s potential to improve the productivity of category managers (Dugundji et al., 2024).

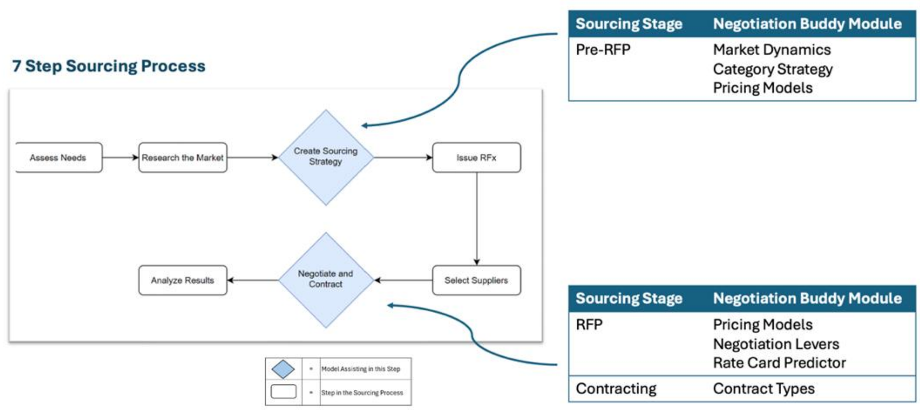
Another notable use case is an autonomous negotiation tool. As previously mentioned, the global retail corporation, Walmart, launched an AI-powered chatbot pilot in 2021 using Pactum AI software that negotiated with suppliers. The initiative targeted tail-spend categories—those with low value but high volume—and focused on suppliers where sufficient data on payment terms existed. The autonomous negotiation pilot resulted in a 1.5% reduction in spend and extended payment terms by an average of 35 days. Notably, the tool will run more efficiently over time, learning from each negotiation, while handling up 2,000 negotiations at once (Hoek et al., 2022).

2.7 Synthesis and Application

Despite the abundance of literature on category management, negotiation frameworks, and procurement automation, few existing tools operationalize these theories into an integrated, data-driven system for use in real-time negotiation support. This research addresses that gap by introducing the Negotiation Buddy —an application that fuses strategic sourcing theory (e.g., Kraljic’s Matrix and Porter’s Five Forces) with unsupervised clustering techniques (K-Means clustering) and machine learning models (XGBoost regression) to deliver actionable advice to a procurement professional. The proposed framework seeks to advance procurement decision-making and codify institutional learning by bridging the disconnect between prescriptive sourcing theory and the dynamic negotiation environment faced by today’s teams.

Figure 6 illustrates how the modules in the Negotiation Buddy tool fit into with key stages of the 7-step sourcing process (described in Section 2.5). Each module supports specific sourcing activities—sourcing strategy creation, RFP negotiation, and contracting—by providing tailored insights specific to the user's subcategory, region, and sourcing stage. The qualitative content was sourced from the sourcing frameworks reviewed in the State of the Practice, our sponsor's institutional knowledge (captured through category frameworks and best practice documents), and market intelligence platforms. Further detail of the methodologies used to inform the Negotiation Buddy is provided in the following section.

Figure 6. Integration of the Negotiation Buddy into the 7-Step Sourcing Process



3. Methodology

This section outlines the methodological framework employed in the development of the Negotiation Buddy. The objective is to enhance procurement negotiation outcomes by integrating machine learning techniques with strategic sourcing frameworks. The approach combines unsupervised and supervised learning methods to identify negotiation patterns in spend data, educate the user on category management strategies, and provide predictive insights. This structured methodology ensures a data-driven approach that aligns with best practices in supply chain management and procurement analytics. The following sections detail the selected methodologies, the data processing pipeline, and their application within the research framework.

3.1 Identifying Needs and Objectives

Collaborating with our sponsor company revealed a pressing need to support sourcing professionals that are less experienced or those navigating new categories. These individuals often lack the nuanced understanding required for complex sourcing events and negotiations. To address this gap, we designed a Negotiation Buddy Framework that integrates unsupervised clustering algorithms with a supervised predictive machine learning model to support procurement negotiation strategies.

- Clustering (K-Means): It segments historical negotiation data using K-Means clustering, based on agreed prices along with categorical and numerical features. This reveals behavioral and pricing patterns across supplier-role combinations. .
- Prediction (XGBoost): It uses an XGBoost regression model to predict the agreed price in future negotiations. The prediction is based on updated categorical and numerical features—including the cluster assignment—allowing for more targeted and data-informed negotiation planning.

3.2 Framework Selection and Analytical Techniques

The methodology builds on the six key areas reviewed in the State of the Practice: category management, supplier segmentation, market analysis frameworks, sourcing levers, negotiation techniques, and automation technology. Specifically, this project applies three methods highlighted in the review—Kraljic's Matrix, Porter's Five Forces, and emerging automation technologies—and adapts them with machine learning models to create an intelligent decision-support tool. Kraljic's Matrix is used as the foundation for the risk/value category classification, while Porter's Five Forces supports market analysis at the subcategory level. Automation techniques are incorporated through the design of ML-based clustering and regression models that enhance negotiation performance.

To adapt these methods for use in the Negotiation Buddy, we implemented the following:

- Kraljic's Matrix is implemented through a guided process that combines user input with research-based heuristics and procurement best practices. This approach enables the Negotiation Buddy to classify the user's subcategory at hand based on its business value and supply risk in a consistent and strategic manner.
- Porter's Five Forces is operationalized through structured data using sponsor-provided market intelligence tools that translate key market dynamics—such as supplier power or competitive rivalry—into quantifiable data inputs.

Automation techniques are applied via clustering (KMeans) to identify behavioral and pricing patterns across supplier-role combinations and predictive modeling (XGBoost), allowing the Negotiation Buddy to anticipate supplier rate card values and recommend optimal negotiation actions.

Analytical Techniques

A combination of analytical techniques were selected for its ability to generate useful sourcing and negotiation advice for the user. The subsections below describe each technique, with a summary provided in Table 1 below.

Clustering Analysis (K-Means)

- Applied to historical RFP data to identify natural groupings in negotiation data.
- Enabled segmentation of suppliers and roles into groups based on pricing tendencies.
- Provides unsupervised learning insights without predetermined categories.

Dimensionality Reduction Techniques

- Employed t-SNE (t-Distributed Stochastic Neighbor Embedding) and UMAP (Uniform Manifold Approximation and Projection) to visualize high-dimensional clustering results, which help confirm meaningful separation.
- Assist in stakeholder interpretation of complex supplier segmentation patterns through intuitive 2D plots.

XGBoost (Gradient Boosting)

- Selected for its powerful predictive capabilities in modeling negotiation outcomes.
- Well-suited for handling complex, non-linear relationships in procurement data.
- Provides insights into feature importance, which helps in strategic decision-making.

SHAP (SHapley Additive exPlanations)

- Used to explain how individual negotiation outcomes were predicted by the model.
- Improves transparency and enables the user to understand which input variables most influenced the predicted rate card values.

Table 1. Summary of Analytical Techniques

TECHNIQUE	PURPOSE/FUNCTION	BENEFITS
Clustering Analysis (K-Means)	Identify natural groupings in RFP data; segment suppliers based on pricing behaviors.	Unsupervised pattern discovery without prior labels.
Dimensionality Reduction Techniques	Visualize high-dimensional clustering results and assist interpretation via 2D plots.	Enhances understanding of supplier segmentation.
XGBoost (Gradient Boosting)	Model complex relationships in procurement data and predict negotiation outcomes.	Supports strategic decisions with predictive insights.
SHAP (SHapley Additive exPlanations)	Explain model predictions by quantifying the impact of each feature on the output.	Improves model transparency and user trust.

3.3 Data Processing Pipeline

The data processing pipeline was designed to transform raw supplier and macroeconomic data into structured inputs suitable for both clustering and supervised machine learning models. This process included data cleaning, feature transformation, the construction of model-ready datasets using pipelines, training the data, and incorporating the clusters.

(1) Data Cleaning and Filtering

- The dataset was sourced from the sponsor’s historical RFP data in the IT App Development subcategory in the China Region, spanning the years 2020, 2022, and 2024.
- Observations with missing values in the target column were removed to ensure clean inputs for modeling.

(2) Feature Selection and Engineering

- Two distinct sets of features were created for clustering and prediction tasks. These included supplier-specific attributes (e.g., Supplier, Roles, Experience), event-level features (e.g., Year), and macroeconomic indicators (e.g., Delta PPI, Delta GDP, Delta Electricity, Delta Labor, Inflation).

- A cluster label, generated from the K-Means model, was appended to the supervised learning feature set to enhance context awareness in rate card prediction.

(3) Transformation with Pipeline Encoders and Scalers

- Categorical variables such as supplier and role information were encoded using OneHotEncoder.
- Numerical features were standardized using StandardScaler to ensure comparability and improve model performance.
- Transformation pipelines were applied separately for clustering and supervised learning models to accommodate slight differences in feature sets.

(4) Dimensionality Reduction

- After preprocessing, dimensionality reduction techniques (UMAP and t-SNE) were applied to the transformed feature space.
- These techniques enabled effective visualization of high-dimensional data, supporting the validation of clustering results.

(5) Training and Evaluation Splits

- The processed dataset for supervised learning was split into training and testing sets using an 80/20 split via train_test_split.
- Cross-validation was employed during model training to assess performance stability and minimize overfitting.

(6) Integration of Clusters

- Outputs from the unsupervised clustering model were used as additional input features in the predictive modeling stage.
- This integration enabled the Negotiation Buddy to leverage insights from both behavioral segmentation and economic forecasting.

3.4 Application of Methodology

The Negotiation Buddy is designed to support procurement agents by integrating a structured category mapping framework based on risk and value to the business. This framework offers strategic recommendations on best-in-class approaches for conducting Requests for Proposals (RFPs). Additionally, the tool aggregates category- and region-specific data, which informs machine learning models that predict expected rate card proposals from suppliers. These predictions enable procurement teams to assess whether further negotiations are necessary or if the best possible rate has already been achieved.

To ensure optimal category mapping, the Negotiation Buddy incorporates a logic-based algorithm aligned with Kraljic's Matrix, facilitating the identification of procurement strategies that maximize value while mitigating risk exposure. Moreover, it applies Porter's Five Forces analysis to evaluate market conditions and recommend category management strategies tailored to each procurement scenario.

Beyond strategic methodologies, historical RFP data is leveraged to train an unsupervised clustering model (K-Means), which determines the optimal segmentation of rate cards. The clustering model utilizes historical rates and procurement-related variables, including supplier name, role, role experience, and year. The clustered dataset is subsequently used to train a supervised regression model (XGBoost), which predicts rate cards for new RFPs. These predictions account for negotiation timing and macroeconomic influences, allowing procurement teams to make informed, data-driven decisions that enhance negotiation outcomes.

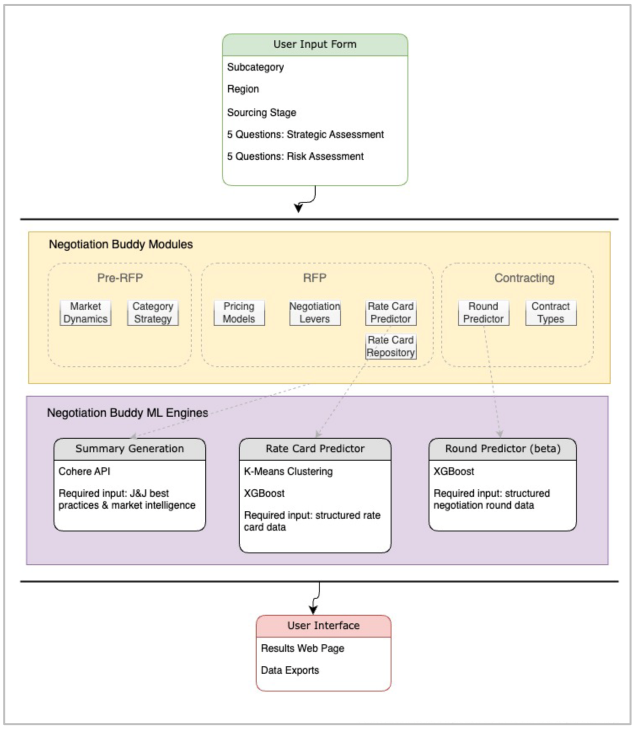
Given the complexity of procurement negotiations, various factors influence their structure and execution, including the number of conflicting priorities, dependencies between these issues, representation of utility, negotiation protocol, form (bilateral or multi-party), and time constraints (Ito et al., 2009).

Our research on sourcing technology services has identified key determinants of effective negotiation strategies, which have been systematically incorporated into the model's structure:

- Risk/Value Category Mapping (Kraljic's Matrix)
- Spend Analysis
- Market Analysis (Porter's Five Forces)
- Negotiation Protocols
- Identification of Negotiation Attributes and Utilities

These determinants were structured into seven modules, depicted in Figure 7. The diagram illustrates the overall architecture of the tool including the user input form, modular workflow across sourcing stages (Pre-RFP, RFP, and Contracting), machine learning engines, and the end user interface. It highlights how the supply chain frameworks and the predictive models are organized in easily navigable modules. The intention was to present relevant negotiation insights to users through a dashboard with exportable results.

Figure 7. Architecture of the Negotiation Buddy Tool



By integrating these methodologies, the Negotiation Buddy provides procurement professionals with a data-driven approach to supplier negotiations. The combination of unsupervised and supervised learning models ensures that both pattern discovery and predictive capabilities contribute to the provided negotiation strategies, enhancing procurement effectiveness and cost efficiency.

3.5 Model Architecture

The model comprises four interdependent mechanisms: the Classifier, Clustering Engine, and Predictor.

A. Classifier Mechanism

This component gathers critical inputs from both the user and external sources to perform category mapping and generate tailored negotiation levers and guidelines, forming a strategic playbook to support the user throughout the RFP process.

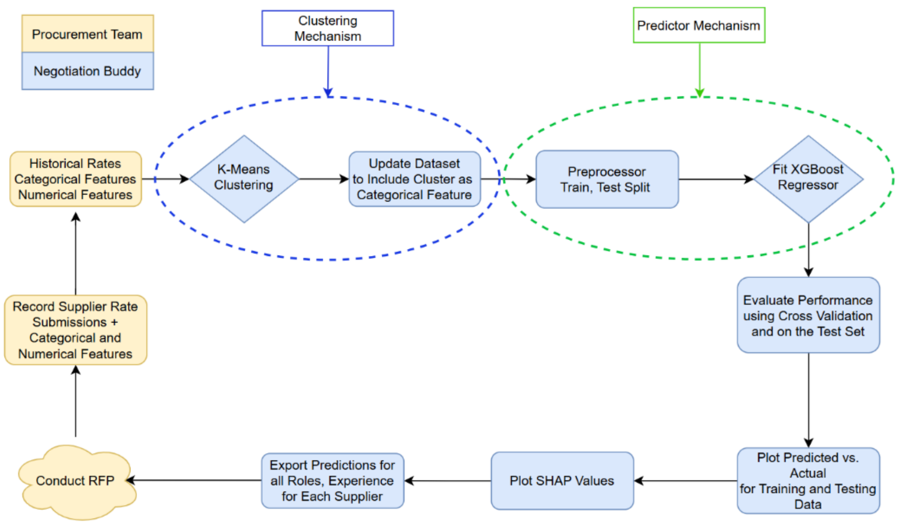
B. Clustering Mechanism

This component employs unsupervised machine learning to identify patterns and group data points based on similarity. Using K-Means clustering, it iteratively refines cluster centroids to minimize intra-cluster variance, effectively uncovering hidden relationships within the data that may not be immediately apparent. This method draws inspiration from the work of Lahtinen (2021), who applied clustering to categorize material suppliers based on their procurement behavior.

C. Predictor Mechanism

By leveraging the clustered data, we can enhance a supervised predictive model like XGBoost by incorporating the cluster assignments as categorical features. This improves the model's performance on both training and testing data, increasing its predictive accuracy and robustness. By grouping similar data points, the model gains a deeper understanding of underlying patterns, allowing it to make more precise predictions. This approach is particularly valuable when dealing with complex procurement data, where supplier pricing trends may not be immediately apparent. As discussed in section 3.2, this component plays a crucial role in forecasting supplier rate cards for the year in which the RFP will be conducted, enabling more data-driven decision-making in the sourcing process.

Figure 8. Negotiation Buddy Machine Learning Model



Our model applies an unsupervised learning approach to segment suppliers based on historical rate card data and macroeconomic indicators using clustering techniques. The preprocessing pipeline transforms both numerical features and categorical attributes before fitting a K-Means clustering algorithm. To determine the optimal number of clusters, the model evaluates both inertia and silhouette scores across a range of cluster values. Figure 8 illustrates the model's architecture, showing the flow from data ingestion and preprocessing to clustering and evaluation, providing a structured framework to identify distinct supplier behavior patterns and rate trends.

3.6 Techniques for Optimizing Negotiation Outcomes

The following techniques represent key components of our model's structure, designed to enhance procurement decision-making and negotiation strategies through advanced methodologies and machine learning integration.

Strategic Sourcing Strategy

Our framework promotes a structured, data-driven procurement methodology, leveraging comprehensive market and value-risk analyses. This strategy guides procurement agents in selecting the most effective negotiation protocol that defines the formal interaction between the negotiators: whether the negotiation is done only once (one-shot) or repeatedly, and how the exchange of offers between the agents is conducted (Ito et al., 2009).

Machine Learning Integration

The core strength of the Negotiation Buddy lies in its integration of machine learning into the procurement decision-making workflow. The model begins with unsupervised clustering to segment suppliers based on behavioral pricing trends. These segments provide foundational insights that inform negotiation strategy.

The model then uses XGBoost to predict rate card outcomes for future RFPs, leveraging both the original data and the cluster labels to capture nuanced relationships. To ensure interpretability, SHAP values are applied to highlight which features have the most influence on each prediction—bridging the gap between algorithmic complexity and practical decision-making. Together, these techniques provide procurement teams with both high-performance prediction capabilities and transparent, explainable insights.

Machine learning enables the system to train and refine utility-strategy pairs continuously. By incorporating deep learning within the classifier mechanism, we could enhance the accuracy of opponent behavior predictions.

Continuous Improvement

By analyzing historical negotiation data, the framework continuously refines its recommendations. This ensures that procurement tactics evolve in alignment with organizational goals and dynamic market conditions, driving long-term strategic success. To maintain relevance and improve predictive performance, the Negotiation Buddy must evolve through continuous improvement mechanisms:

1. Data Expansion: Increasing temporal coverage beyond 2020–2024 and incorporating broader sourcing categories will improve robustness and generalizability.
2. Live Data Integration: Incorporating real-time external feeds (e.g., commodity indices, labor market trends) will enhance model responsiveness and accuracy under dynamic market conditions.

3. Operational Feedback Loops: Embedding the tool into live sourcing events and collecting user feedback will support retraining and contextual refinement.
4. Algorithmic Advancements: Future iterations may incorporate reinforcement learning or transformer-based models to process negotiation transcripts and simulate interactive negotiation behavior.

These enhancements will ensure that the Negotiation Buddy continues to deliver strategic value, adapts to new procurement environments, and supports enterprise-wide adoption.

4. Results and Discussion

This section presents the key findings gathered during the development of the Negotiation Buddy. It begins with an analysis of supplier clusters, model performance, and feature insights. Next, it presents the user interface and the design considerations taken to integrate modules in a user-friendly experience. Finally, it evaluates the tool's implications and limitations in a procurement context.

4.1 Results

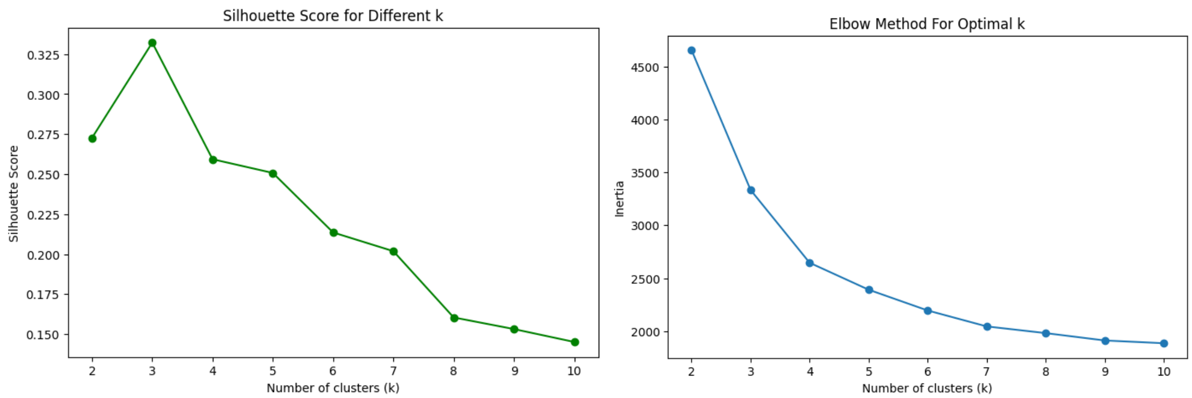
Collectively, the model's results demonstrate its ability to uncover hidden patterns in supplier pricing, generate accurate predictions, and provide transparent reasoning behind its outputs—laying a strong foundation for strategic sourcing and data-informed negotiation planning.

Clustering Performance

K-Means clustering was applied to historical rate card data to segment suppliers based on behavioral pricing tendencies. The optimal number of clusters was selected based on the silhouette score evaluation and elbow method. As shown in Figure 9, the maximum score occurred at $k = 3$, supporting the selection of three distinct supplier segments.

Figure 9. Two Methods for Determining Various Cluster Sizes *(k)*

(a) Silhouette scores (b) The Elbow Method



Clustering Characteristics

The clustering analysis aimed to group similar entities based on their 'Supplier-Role', 'Experience', and historical 'Rate_Card' values for the years 2020, 2022, and 2024. These features were selected to capture the combined influence of supplier identity, role specificity, experience level, and historical pricing trends on the formation of distinct groups. The resulting clusters represent coherent patterns in supplier-role combinations, experience profiles, and rate card trajectories over time.

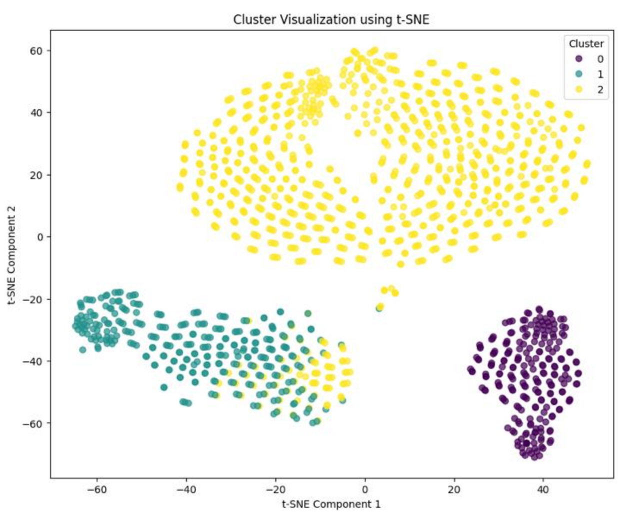
The 'Supplier-Role' feature served as the primary categorical dimension, enabling segmentation based on unique combinations of supplier and role. 'Experience' added a second layer of granularity, differentiating entities further by seniority level. The numerical rate card values across the three years were used to capture cost trends, helping to distinguish entities with similar pricing evolution, even if their absolute rate levels differed. As a result, the model grouped entities not just by static cost but by directional similarity in rate changes, an insight particularly useful for pricing strategy and supplier benchmarking.

To determine the optimal number of clusters, two key evaluation metrics were used: inertia and silhouette score. Inertia measures the internal cohesion of clusters, specifically the sum of squared distances between each point and its assigned cluster centroid. Lower inertia indicates tighter, more cohesive clusters. However, inertia tends to decrease as more clusters are added, which can lead to overfitting. Silhouette score, on the other hand, balances intra-cluster cohesion with inter-cluster separation. It ranges from -1 to 1, where higher values indicate that data points are well-matched to their own cluster and poorly matched to neighboring clusters.

By analyzing both metrics in tandem, we ensured that the chosen number of clusters offered a balance between granularity and interpretability—capturing meaningful differentiation without fragmenting the data excessively. This approach enabled us to uncover actionable patterns within the supplier-role landscape that can inform downstream modeling and strategic decisions in sourcing and negotiation.

Figure 10 presents a t-SNE visualization of the clustered supplier-role data. The clear separation among clusters confirms the model's ability to identify meaningful distinctions across supplier pricing behavior and role characteristics. Cluster 2 (yellow) displays a wider, more dispersed distribution, suggesting greater variability in supplier pricing strategies or responsiveness to macroeconomic shifts. In contrast, Clusters 0 (purple) and 1 (teal) exhibit tighter cohesion, indicating more consistent pricing patterns. These visual patterns validate the cluster groupings and support their use for strategy tailoring, supplier differentiation, and pricing scenario planning.

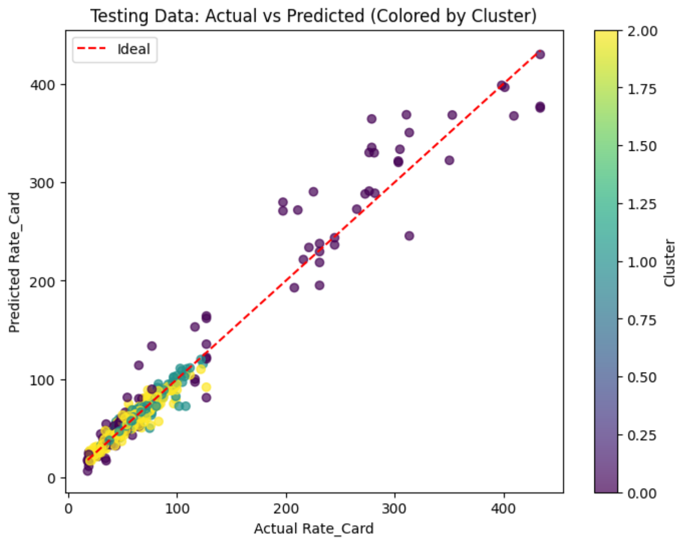
Figure 10. Cluster Visualization using t-SNE



Model Accuracy and Prediction Performance

XGBoost was trained on the segmented and preprocessed dataset to predict supplier rate card values. Model outputs closely matched observed test data values. Figure 11 below shows the actual rate card values against the predicted rate card values. The model's clusters are color-coded, with the red dashed line indicating perfect prediction alignment.

Figure 11. Actual versus predicted rate card values on test data.



The Negotiation Buddy demonstrated strong predictive performance during cross-validation. The model achieved a mean R^2 score of 0.96, which means it explains approximately 96% of the variance in the target variable. The corresponding mean MAE (Mean Absolute Error) was 6.80, and the MAPE (Mean Absolute Percentage Error) was 9.38% suggesting a high degree of accuracy with low average prediction error.

Feature Influence and Interpretability

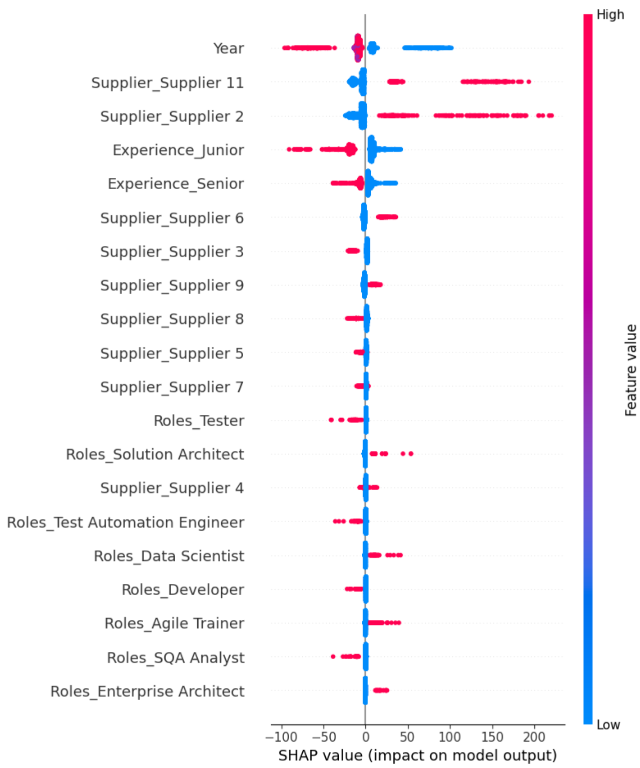
SHAP values were computed to identify the most influential factors driving rate card predictions (see Figure 12). The top contributors included Year, Supplier Identity, and Experience Level, confirming that time, supplier behavior, and seniority significantly shape predicted outcomes.

The Year feature had the greatest overall impact. Interestingly, lower year values (e.g., 2020, shown in blue) tended to increase rate card predictions, while higher year values (e.g., 2024, shown in red) generally decreased them. This counterintuitive trend may reflect pricing adjustments, sourcing shifts, or external cost pressures not uniformly passed through to rate cards in recent years.

Among suppliers, Supplier 2 and Supplier 11 showed consistently strong positive SHAP values, indicating they are associated with higher predicted rates compared to peers. Other suppliers exhibited more moderate or inconsistent effects, suggesting varied pricing strategies or inconsistent historical behavior.

Experience Level was also a strong driver: Junior experience (blue) typically reduced predicted rates, while Senior experience (red) contributed positively, aligning with expectations around labor cost differentials. Role-specific features such as Data Scientist and Solution Architect also had positive impacts on predictions, while roles like Tester and SQA Analyst showed smaller, more dispersed effects. The narrow or wide spread of SHAP values across roles reflects the variability or consistency of rate trends for each function.

Figure 12: SHAP Summary Plot of Feature Influence on Model Output



Together, these insights provide a transparent view of how the model reaches its predictions, enhancing user confidence and enabling more informed sourcing decisions.

4.2 User Interface

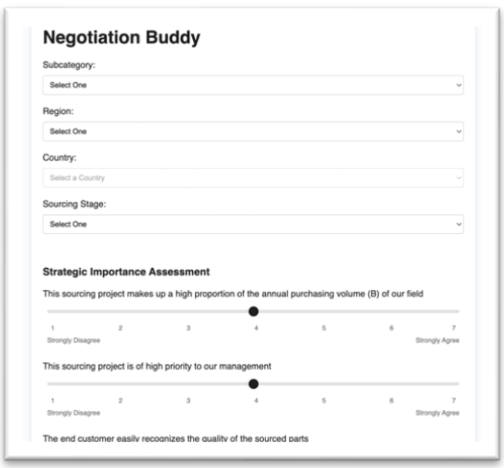
A few key considerations were prioritized in the development of the user interface. According to stakeholder conversations, it was critical that the tool (1) be easy for a new procurement professional to use and intuitively navigate, (2) allows users to complete the input dashboard in under ten minutes, and (3) enable users to easily edit previous responses to see how new inputs would affect the outputs. We also incorporated color and visualizations—such as plots and tables—to add visual interest to the stream of negotiation advice presented to the user.

The walkthrough of the user interface is as follows:

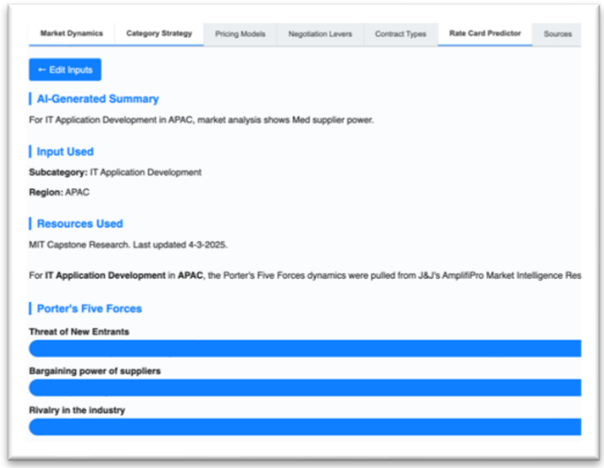
1. On the introduction page ("Input Dashboard"; see Figure 13 (a)), the User is presented with 14 questions covering the User's subcategory, region, country, sourcing stage, five questions that assess the subcategory's strategic importance, and five questions that assess the subcategory's risk to the company. It is expected that these questions can be answered in five minutes, even by users with beginner-level knowledge of the subcategory. Upon completion, the user presses the "Generate Strategy" button at the bottom of the page.
2. This triggers the page to transition to the "Output Dashboard" (see Figure 13 (b)). The tabs at the top of the screen layout the six modules: Market Dynamics, Category Strategy, Pricing Models, Negotiation Levers, Contract Types, Rate Card Predictor. According to the User's selected Sourcing Stage, the most relevant module tabs are highlighted, signaling to the User to start with these tools. However, the User can explore any module she desires, and the presented negotiation advice is tailored to her subcategory and region. There is an additional tab that lists the sources used in each module. Each of the heuristic-powered modules (Market Dynamics, Category Strategy, Pricing Models, Negotiation Levers, Contract Types) have the following top-to-bottom layout: an "AI-Generated Summary" to provide a high-level summary of the recommendations, "Input Used" to explain which inputs were taken into consideration, "Resources Used" to show where the advice came from and to build trust, and finally the full recommendations.
3. At any time, the User can press the "Edit Inputs" button to go back to the Input Dashboard to engage with different negotiation perspectives.
4. The Round Predictor was placed in its own dashboard for easier adjusting and debugging.

Figure 13. Screenshots of the Negotiation Buddy User Interface

(a) Input Dashboard



(b) Output Dashboard



4.3 Limitations

While the framework delivers meaningful insights, the following limitations should be acknowledged:

A. Temporal limitations: Data is constrained to three years (2020, 2022, and 2024), which limits its ability to capture long-term trends, economic cycles, or structural changes in procurement behavior. This constraint can affect the model's robustness in forecasting future demand patterns or negotiation outcomes, particularly in response to macroeconomic shocks or new suppliers.

B. Macroeconomic sensitivity: Inputs like inflation and GDP are subject to lag and regional variation, potentially limiting accuracy in real-time applications.

C. Cluster dependency: Clustering outcomes are influenced by selected features and may not generalize to all supplier types or categories without re-tuning.

Future improvements may include expanding the dataset to include diverse sourcing subcategories, incorporating live market feeds, and validating performance through real-world pilot tests with procurement teams to ensure the model delivers actionable insights in practice.

5. Conclusions

This capstone project demonstrates how data-driven tools can transform the negotiation process within procurement organizations. By embedding advanced analytics into the sourcing workflow, the Negotiation Buddy prototype supports procurement professionals in uncovering strategic levers and improving negotiation consistency, especially in categories where institutional knowledge may be fragmented or lost due to personnel transitions.

The integration of unsupervised clustering techniques and machine learning predictive models (K-Means clustering and XGBoost) provided actionable insights from historical RFP and macroeconomic data. Clustering segmented suppliers into distinct pricing behavior groups, revealing otherwise obscured patterns that procurement teams can use to inform negotiation strategy. The predictive model achieved high accuracy (MAPE = 9.38%) in forecasting rate card values and highlighted key drivers such as supplier, role, and negotiation year through SHAP analysis. These outputs not only equip procurement professionals with realistic price expectations but also help uncover the underlying factors driving cost variations.

The Negotiation Buddy framework advances procurement practice by structuring sourcing strategy and highlighting negotiation recommendations tailored to the specific dynamics of each event. It does so by:

- Systematically mapping category risk and value using Kraljic's Matrix
- Embedding market analysis via Porter's Five Forces
- Segmenting suppliers through unsupervised learning
- Forecasting rate cards using supervised prediction enriched by macroeconomic context
- Enhancing transparency through model interpretability tools

Together, these features position the Negotiation Buddy as a foundational enabler of strategic sourcing excellence. By combining theory, data, and real-world negotiation patterns, the tool enhances short-term decision quality while fostering long-term institutional learning. A key strength lies in its built-in feedback loops, which capture outcomes from actual negotiations and continuously retrain the model using real data-ensuring the tool evolves with supplier behavior, market conditions, and internal priorities. As procurement becomes increasingly digitized, the Negotiation Buddy offers a scalable solution to preserve organizational knowledge, reduce reliance on individual expertise, and deliver more consistent, data-informed outcomes across sourcing categories and regions. Despite limitations related to the time span of available data and the generalizability of results across categories, this proof of concept validates the potential of intelligent, learning-based decision-support tools in procurement. With continued refinement and expanded data integration, the Negotiation Buddy can serve as a foundational element in digital sourcing transformation, enabling procurement teams to approach negotiations with greater confidence, accuracy, and strategic alignment.

5.1 Management Recommendations

To support the successful adoption and scaling of the Negotiation Buddy, we recommend the sponsor organization implement the following actions:

1. Integrate the tool into the RFP process as a guided decision-support assistant: Position the Negotiation Buddy as a strategic augmentation to existing procurement workflows, not as a replacement. By assisting professionals during RFP evaluations and supplier negotiations, the tool can enhance decision-making while preserving established processes, thereby fostering trust and encouraging consistent use.

2. Launch pilot deployments in high-volume, strategically relevant categories: Begin with IT and application development, where the model was initially trained, and expand to comparable regions to validate performance across geographies. Use these pilots to gather practical feedback, confirm model effectiveness, and guide refinements before scaling to adjacent categories with similar data structures.

3. Develop training programs and interactive dashboards to enhance model transparency: Equip users with clear, intuitive tools, such as SHAP-based visualizations, to explain how predictions are generated and which inputs influence outcomes. This transparency will support user confidence and accelerate adoption across the procurement team.

4. Align adoption incentives with performance metrics: Encourage usage by linking the tool to measurable procurement KPIs such as sourcing cycle time, negotiation effectiveness, and

adherence to category strategies. To reinforce the tool's value, implement a structured process for capturing and reviewing real negotiation outcomes. Integrating this data into the model will strengthen feedback loops, enhance prediction accuracy over time, and demonstrate measurable impact, driving both behavioral change and continuous improvement.

5. Foster cross-functional collaboration between data science and sourcing professionals: Ensure continuous alignment between category managers and technical teams to refine the model based on real-world negotiation dynamics. This collaboration will help maintain relevance, address evolving procurement needs, and support long-term tool effectiveness.

5.2 Future work

To ensure continued success, the Negotiation Buddy should be expanded with additional data sources, including real-time market feeds and more granular supplier data. Continuous refinement through feedback loops will enhance the model's adaptability and improve its predictive accuracy. Integrating advanced features such as Kraljic's category label (non-critical, leverage, strategic, or bottleneck) over time and Porter's five forces supplier classification (Supplier power: low, low-medium, medium, medium-high, high) over time can improve the tool's long-term value.

The team identified the following opportunities to improve the tool to reach the sponsor's procurement goals:

A. Establish an integrated data repository to support ongoing model refinement and scalability

A key next step is to develop a centralized data repository that seamlessly integrates with the sponsor's existing sourcing platforms. This repository will enable the structured capture of supplier-related data throughout the sourcing process, including proposal submissions, negotiation rounds, contract outcomes, and performance metrics. By standardizing and automating data collection at each stage, the repository will ensure consistent, high-quality inputs for the Negotiation Buddy framework. Over time, this will enhance the model's predictive accuracy, support continuous learning, and reduce the manual effort required to prepare data for future sourcing events.

B. Integrate a Large Language Model (LLM)

A valuable area for future development is the integration of a Large Language Model (LLM) to enhance insight generation, model interpretability, and cross-functional collaboration. This will streamline the extraction and synthesis of both internal and external category intelligence. The LLM would automate the aggregation of data sources, such as market trends, supplier reports, and internal strategy documents, enabling sourcing professionals to quickly access synthesized, context-rich insights in a business-friendly format.

Moreover, the LLM will enhance the interpretability of the Negotiation Buddy's predictive outputs, particularly by translating technical elements such as SHAP analysis into actionable insights. This will allow users to understand the key drivers behind the model's recommendations and performance metrics, thereby increasing trust and usability among procurement teams.

Additionally, we propose integrating this effort with the MIT capstone project titled *AI-powered RFx Intelligence for Strategic Supplier Excellence*, which focuses on unstructured data ingestion and classification. The collaboration would serve two purposes: (1) enable automated data extraction and preparation for input into the Negotiation Buddy, and (2) provide users with access to historical negotiation outcomes, surfacing analytical patterns and trends that can inform future sourcing strategies. This unified approach has the potential to create a more intelligent, end-to-end procurement support system.

C. Review and update the sourcing levers algorithm to align with evolving strategic and market realities

To maximize the Negotiation Buddy's long-term relevance and effectiveness, the sponsor's management team should periodically review and refine the sourcing levers algorithm embedded within the framework. This algorithm, which currently recommends negotiation actions based on Kraljic's Matrix positioning and Porter's Five Forces supplier classification, must remain adaptable to shifts in business priorities, market dynamics, and procurement best practices.

We recommend a structured governance process in which cross-functional stakeholders, including category managers, finance, legal, and supplier relationship owners regularly evaluate the validity and impact of the recommended levers. These reviews should challenge existing assumptions and incorporate recent changes in the external market (e.g., supply base consolidation, regulatory shifts) and internal strategy (e.g., sustainability goals, digitalization initiatives, risk tolerance).

By maintaining alignment between the algorithm's logic and the sponsor's sourcing objectives, this practice will ensure that the Negotiation Buddy continues to provide actionable, context-aware recommendations that reflect best-in-class strategic sourcing behaviors. This ongoing calibration will also support greater user adoption and confidence in the tool's outputs.

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