Optimizing Procurement in Hospitality: Developing an Intelligent Alert System for Cost-Effective Purchasing

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Abstract: Through the provision of real-time pricing alerts, this project seeks to develop a procurement alert system that will improve decision-making and cost-efficiency in the hospitality industry. By integrating with existing databases, the system will deliver actionable insights thorough data analysis, enabling businesses to make well-informed purchasing decisions that could lead to significant financial benefits. The project will be implemented through a structured methodological approach, including impact assessment, feasibility studies, and prototyping, with a strong emphasis on data security, privacy, and ethical considerations. The final system is anticipated to dramatically enhance supply chain responsiveness, lower costs, and improve procurement efficiency, setting up the hospitality sector for long-term growth in a competitive marketplace. This project aims to strategically use technology to address historical procurement challenges, contributing to academic research and real-world restaurant management applications.

Keyword: Procurement alert system, Cost Efficiency, Real time pricing alert, Decision making, Hospitality sector

1. INTRODUCTION

Effective procurement procedures are crucial for retention of customers and company expansion in today's competitive business climate [1]. A study done in the healthcare sector revealed a worrying trend where an alarming 54% procurement non-compliance rate, which is causing shortages of necessary drugs. This not only put the patients care in danger but also uncover broader issues [2]. This narrative functions as a cautionary tale, emphasising the pervasive consequences of procurement processes that fall short of expectations. This lesson is understood by the restaurant industry. Purchasing is a critical function that guarantees chefs have the premium ingredients they require to satisfy customers on a daily basis. But when procurement goes wrong, it can compromise menus, cause delays in meals, and ultimately put customer loyalty to the test—whether due to inefficiencies, a lack of transparency, or misaligned organisational beliefs.

A major challenge in the field of procurement is the ongoing lack of transparency related to prices, which can mask the actual cost of goods and result in expensive choices. The importance of solving pricing discrepancies and optimising procurement procedures is highlighted by this inefficiencies. Efficiency can be greatly increased through performance monitoring and aligning organisational beliefs, according to recent research in public procurement [3]. For example, a study using a new e-procurement system in Chile discovered that making managers aware of performance reports that were randomly assigned resulted in significant cost savings up to a 15% decrease in overspending—by encouraging more economical purchasing practices [3].

Understanding the similarities with the restaurant sector, the purpose of this study proposal is to use technology to address procurement inefficiencies, specifically through improving price transparency and streamlining effective price comparisons. Through a comprehensive analysis of public sector procurement strategies and private sector customer behaviour, this study aims to optimise purchasing strategies, drive cost savings, and promote sustainable growth within a dynamic market environment. In addition to increasing operational effectiveness, addressing these issues supports the company's main goal of preserving customer satisfaction and competitiveness in a market that is changing swiftly.

2. RESEARCH OBJECTIVES

Our research's primary objective is to create an intelligent alert system that will improve the restaurant industry's procurement efficiency. Real-time pricing tracking is a feature of this system, guaranteeing that companies have access to the most recent price information. It will make it easier to compare prices between various suppliers and customers, which will aid in determining the most advantageous pricing options. The system's goal is to drastically lower procurement costs by warning companies about possible cost-saving measures. It will also improve price visibility throughout the market, providing a more clear picture of price trends and fluctuations. In the end, the system aids in procurement strategy optimization, facilitating better decision-making and increased overall cost effectiveness. Through these capabilities, the alert system will assist restaurants in making strategic procurement choices, consequently improving operational effectiveness and cost management.

3. RELATED WORK

Historically, procurement has developed from a purely supportive role to a key strategic element that is essential to the success and competitiveness of many industries, including the hospitality sector. One of the earliest scholars to recognise the importance of procurement in controlling long-term supply chains, variable expenses, and raw material shortages was Gee (1975) [5]. His study emphasised the importance of procurement in obtaining operational efficiency and the necessity of competent management to strike a balance between operational demands and market uncertainties.

Building on Gee's significant work, recent studies have investigated how procurement inefficiencies present major challenges in a variety of industries. For example, when BP Magadzire (2017) looked into procurement inefficiencies in the healthcare industry, they found serious repercussions like drug stock-outs in South Africa [2]. Similar to this, research on the Roads and Highways Department (RHD) in public sector procurement reveals inefficiencies in civil work contracts. These deviations from the engineer's estimates, which can reach 29.306%, are the result of political pressure, obsolete rate schedules, and collusion, among other issues. These findings indicate significant inefficiencies[6]. These studies highlight the fact that procurement issues affect more than just one industry; they also have an impact on the hotel and restaurant sectors. The idea that improved performance monitoring and price transparency can greatly increase procurement efficiency is supported by real-world evidence. For instance, studies on public sector e-procurement systems reveal that performance monitoring can cut overspending by as much as 15% [3]. These results imply that by implementing these concepts, the restaurant industry can see comparable improvements.

Insights from public sector studies, like those on the e-procurement systems in Chile, offer important insights into the advantages of managerial supervision and performance monitoring in promoting cost efficiency [3]. Furthermore, the RHD study draws attention to particular inefficiencies like the propensity to select the lowest-bidders for contracts, the absence of contractor databases, and protracted bureaucratic procedures [6]. Despite being based on data from the public sector, these insights can be used to comprehend comparable problems in the private sector, especially in the restaurant business. Research reveals persistent problems in the private sector, including disparities in prices and ineffective supplier management. These concerns are particularly pertinent to the restaurant sector, as ineffective procurement practices can have an impact on operational results. Beyond conventional procurement techniques, more sophisticated and customised strategies are needed to address these issues.

Although previous research has provided valuable insights, there is a noticeable deficiency of studies that specifically address the restaurant industry and integrate real-time price tracking, supplier comparison, and performance monitoring. There is a knowledge gap about how these tactics can be modified to fit the particular requirements of restaurants because the majority of research has concentrated on public procurement or larger industries. A remedy for these shortcomings is provided by predictive analytics, which is quickly becoming a cutting-edge tool in supply chain management. Predictive analytics allows businesses to manage changes in supply and demand in a proactive manner, surpassing the limitations of traditional reactive models. This strategy resolves issues raised by Gee (1975), and the RHD study by coordinating procurement activities with organisational goals and operational standards [5-6].

Recent studies on AI-driven predictive analytics in the retail industry provide more evidence for this viewpoint. They highlight how these technologies can completely transform procurement by predicting demand trends, streamlining inventory, and customising customer engagement strategies [7]. Predictive analytics' capacity to process enormous volumes of data and deliver insights in real time is especially important for the restaurant business, where variations in supply and demand can have a big impact on operations. This emphasises how crucial it is to incorporate predictive analytics into procurement procedures in order to improve operational effectiveness and decision-making.

The objective of the proposed study is to close these gaps by creating an intelligent alert system specifically designed for the restaurant business. By using predictive analytics to produce useful insights, this system will increase procurement efficiency by improving price transparency and facilitating more informed decision-making. Just as retailers have improved customer satisfaction and operational efficiency through similar technologies [7], the system will allow restaurants to optimise their procurement processes by incorporating the sophisticated AI-driven predictive analytics strategies that have proven successful in the retail sector. The integration of predictive analytics into procurement workflows aims to streamline inventory management and align procurement actions with strategic goals. Moreover, by drawing on successful implementations in retail, the proposed system will not only address the unique challenges of the restaurant industry but also set a precedent for the application of cutting-edge AI technologies in hospitality and beyond.

4. METHODS & EXPERIMENT DESIGNS

Predictive analytics relies heavily on data modelling, where the format, quality, and structure of the input data greatly affect how successful the models are. Using a dataset collected from several Brazilian restaurants, data modelling was used in this study to predict procurement prices and pinpoint possible areas for cost savings. A methodical process for converting unstructured procurement data into a format that is best suited for predictive modelling is shown in this section.

The capacity of data modelling to find patterns and relationships in the data that are essential for producing precise predictions is what gives it its significance. The data needs to be carefully pre-processed in order to capture these patterns. Pre-processing is the process of transforming raw data into a format that is organised, standardised, and informative through the use of data transformation, data cleaning, and feature engineering. This improved dataset serves as the basis for the creation of predictive models that can produce insightful cost-saving forecasts and precise forecasts.

Data Collections and Understanding

The study started with gathering purchase information from a variety of Brazilian restaurants, which was then kept in a MySQL Server database. Given the complexity of procurement data, MySQL was chosen for its strong capabilities in managing and querying large-scale datasets [8]. The dataset included comprehensive purchase data that came from invoices, including supplier information, company-level data, and item specifics like names, descriptions, and categories. The data also included temporal data indicating the date and time of each transaction, along with detailed pricing details like unit prices and total purchase costs. The dataset also contained information about products that the restaurant/company and the suppliers handled differently, illustrating the complex relationships and procedures that exist between these organisations.

To effectively direct the subsequent pre-processing and modelling stages, a thorough comprehension of the raw procurement data was required. In its initial unprocessed state, the dataset represented a range of purchasing behaviours and pricing variability among suppliers. Given the inherent complexity of this raw data, a thorough investigation was required to identify important patterns, anomalies, and regions that would benefit most from pre-processing.

Data Pre-processing

A crucial step in the modelling process is data pre-processing, which makes sure the data is suitable for predictive analysis and of a high quality. This stage is crucial because the precision and consistency of the input data determine how well the predictive models work. The particular pre-processing procedures used in this study are described in detail in the sections that follow. In the pre-processing workflow, addressing dataset inconsistencies was the first step. There were initially 524,809 records in the procurement dataset. But in order to guarantee this raw data's accuracy and dependability for later modelling tasks, it was necessary to refine it.

There were 29,910 duplicate records found in the entire dataset. The main cause of these duplicates was the entry of the missing Invoice dates more than once, which frequently happened as a result of problems like system bugs or human data entry mistakes. Python methods were utilised in order to systematically identify and impute these missing records, thereby reducing the potential bias that these duplicates could introduce into the model training process. A study asserts that the integrity of the data used for model development was preserved by eliminating duplicates to guarantee that every transaction was represented uniquely [9] (refer to Appendix Figure 1 for the percentage distribution graph of the duplicates vs total records).

The existence of missing values, especially in the invoice data, posed a serious obstacle to data cleaning. In particular, 8,830 records had missing invoice numbers, which were found to be a common cause of the previously mentioned duplicate entries. Since the invoice dates served as important identifiers in the dataset, connecting particular orders to procurement transactions, these missing values were extremely important. An imputation strategy was used to address this, mainly substituting the median of the corresponding column for missing values in numerical fields. Since the median is less susceptible to outliers and skewed distributions than the mean, it is a more reliable and representative approximation in situations where the data may be unpredictable or contain extreme values [10]. Although median imputation successfully maintains the data's central tendency, it is acknowledged that if the missing data were not distributed randomly, it may decrease variability and possibly introduce bias. This approach was thought to be the best for preserving data integrity and getting the dataset ready for later modelling phases in spite of these shortcomings[10].

In Conjunction with addressing the missing values, it was crucial to identify and handle outliers to prevent major distortion of model predictions. Box plots and Q-Q plots were two of the statistical techniques used to find and evaluate these anomalies. Box plots gave the data distribution a visual representation and highlighted any possible outliers that did not fall within the interquartile range. To evaluate the data's normality and pinpoint any points that substantially deviated from the expected distribution, Q-Q plots were employed. After outliers were found, the dataset was investigated further to see if these observations were actually anomalies in the market or the result of incorrect data entry.

For columns with highly skewed distributions (refer to Appendix Figure 2), log transformation was applied to lessen the effect of extreme values and stabilise variance throughout the data. The data was transformed to help it resemble a normal distribution (refer to Appendix Figure 3), which improved its modelling suitability. To maintain the integrity of the dataset, outliers that were found to be data entry errors were eliminated, but those that showed true variability were kept. These methods improved the accuracy and dependability of the ensuing predictive models by refining the dataset to ensure it maintained pertinent variability without being unduly influenced by extreme or erroneous values [11].

Exploratory Data Analysis

To thoroughly understand the procurement data and recognize important trends , we had to start our process with exploratory data analysis, or EDA. The goal of this in-depth analysis was not only to comprehend the data on the surface, but also to obtain important knowledge that would influence how our alert system was set up and how our predictive model was developed. We ensured that our model was based on a strong foundation of empirical evidence by carefully examining the data to uncover the underlying factors influencing procurement costs. This allowed us to better focus our feature engineering efforts. Developing a system that could predict prices with accuracy and proactively find cost-saving opportunities required laying this foundation.

We started by analysing purchase trends over various timeframes to discern temporal patterns in procurement behaviour. Finding seasonal trends, growth patterns, and variations in the amount of purchases was the main goal of the analysis. We identified distinct seasonal peaks and low points by charting total purchases over time; these peaks and low points corresponded with known periods of high and low demand within the industry. As an illustration of seasonally driven demand, some items displayed higher purchasing activity during particular months.

The data engineering process, which we used to derive time-related features like year, month, day of the week, and even the quarter in which the purchase happened, was greatly aided by this temporal analysis. The accuracy of price predictions was increased by the predictive model's ability to recognise and take into account these seasonal trends thanks to the addition of these features (refer to Appendix Figure 4 for the purchase trend over time).

Further analysis was done at the company level to understand the purchasing patterns of different entities. We were able to distinguish between businesses with regular buying habits and those with more irregular buying patterns by adding up all of the purchases made by each company over time. Potential outliers and businesses whose purchasing patterns markedly differed from the norm were identified by this analysis. This analysis provided valuable insights that were crucial for customising the alert system. Businesses that showed signs of irregular purchasing were for additional investigation, particularly if their purchase prices differed from expected averages (refer to Appendix Figure 5 for total purchase over time by company).

We also focused on analysing how purchasing prices of companies compared to the average unit price of items in the dataset. Our analysis revealed that a considerable number of businesses routinely paid more than the average for some items. This finding was crucial as it highlighted the potential inefficiency in the procurement processes. The necessity of identifying and notifying procurement teams about these price disparities became evident, leading directly to the development of alert thresholds and the refinement of our predictive model based on the discovery (refer to appendix figure 6 Distribution of companies purchasing above and below average unit prices).

Building upon the findings from the prior studies, we looked more closely at businesses that routinely paid more for their purchases than the average unit price. This investigation looked into their monthly purchasing patterns in an effort to find any trends or explanations for the price increases (refer to appendix Figure 7). For example, unit prices may have increased because some businesses may have been buying in smaller quantities or from suppliers who are less willing to compete. In order to set more accurate and context-sensitive thresholds for alert triggering, it was essential to comprehend these behaviours when configuring the alert system. Because the predictive model was trained to identify these patterns, the generated alerts were precise and useful.

Through the integration of these analyses, a solid foundation was established for the predictive model and the alert system, ensuring that they were customized to meet the unique requirements and difficulties found in the procurement data. Every stage of the EDA was necessary to increase the system's overall efficacy in optimizing procurement procedures.

Feature Engineering

In order to improve the predictive power of models by generating new variables (features) from the raw data, feature engineering is an essential step in the data pre-processing pipeline. This process was guided by domain expertise and deep understanding of the factors that most significantly influence procurement costs, ensuring that the resulting models were both accurate and contextually relevant.

From the available date data, a number of time-related features were designed in order to capture temporal patterns and seasonal trends in procurement. Among them were the extraction of the transaction date's year, month, day, and day of the week. The models' capacity to comprehend weekly patterns, seasonal variations, and long-term temporal patterns improved with the addition of these features, which also increased the models' accuracy in predicting procurement prices over time.

To improve the dataset, multiple new columns were computed in addition to temporal features. To reduce the impact of temporary price fluctuations, the monthly average unit prices for each item, for instance, were computed to provide a normalised measure of pricing trends. In a similar way, the frequency of purchases from each supplier was designed to give an indication of how well the restaurant and supplier got along, as well as potential bulk purchasing agreements. Price volatility, which is determined by the variation in unit prices over time, was another essential component. This attribute gave the models some price stability, which is crucial for projecting future acquisition costs and identifying possible dangers related to price swings.

A number of feature selection methods were used to improve model performance and further refine the dataset. Variance Thresholding was used to remove low variance features, ensuring that only those contributing significantly to the information were retained[12]. The Select K Best technique made it possible to identify the top features most likely to have an influence on the model's predictions by ranking each feature based on its statistical significance [13]. Additionally, Recursive Feature Elimination (RFE) was used to refine the feature set by repeatedly eliminating the least significant variables, leaving only the most predictive ones [14]. Together with the chosen features, these engineered features were meticulously developed to capture important trends influencing procurement costs. A graph highlighting the top ten most important features demonstrated the significance of these features and showed how each feature adds to the model's predictive power (refer to Appendix, Figure 8). By Incorporating this additional context, the predictive models were not only more accurate but also more resilient, capable of delivering insights that are both meaningful and actionable.

Next, Using label encoding, categorical variables (such as suppliers, item and company features) were transformed into numerical form. Because each category is given a distinct numerical value using this method, models that are unable to process categorical data directly can still effectively interpret these features [15]. In order to maintain the natural relationships between categories and guarantee that the categorical data was in a format appropriate for model training, label encoding was used.

Ultimately, data was scaled to a fixed range, usually between 0 and 1, using Min-Max Scaling to standardise numerical features [16]. In particular, for algorithms like gradient boosting machines that are sensitive to the amount of input data, this step was required to guarantee that every feature contributed equally during model training. The model's predictions were less disproportionately influenced by features with wider numerical ranges thanks to scaling.

Model Development and Optimization

To predict the procurement prices and identify cost saving opportunities, several predictive models were evaluated in this study. The selection process focused on the models accuracy and their ability to handle complex , non-linear relationship within the dataset . the models considered were:

Random Forest: To improve prediction accuracy and decrease overfitting, this ensemble approach combines several decision trees. It was selected due to its capacity to provide insights into the significance of features and its resilience in handling a high volume of input features.

K-Nearest Neighbours (KNN): The capacity of K-Nearest Neighbours (KNN) to identify small-scale patterns in the data is assessed. To determine how good KNN was at predicting, it was tested with different parameter configurations.

Decision Tree: Used to explore its potential in capturing non-linear relationships. The Decision Tree model was evaluated for its simplicity and interpretability compared to more complex models.

Gradient Boosting Machines (GBM): Chosen for its iterative method of fixing the mistakes made by inexperienced learners. GBM was an excellent choice because of its adaptability in simulating intricate relationships.

XGBoost: An enhanced iteration of Gradient Boosting, XGBoost gained recognition for its rapidity, efficacy, and capacity for regularisation. Its strong predictive performance and ease of use with high-dimensional data were important considerations in its assessment.

Following model selection, hyperparameter tuning was performed to optimize each model’s performance. Hyperparameters, which were set before the learning process and control the behaviour of the learning algorithms, differ from model parameters, which are learned from the data. Finding the optimal hyperparameters is crucial for maximizing model performance on unseen data.

In this study, hyperparameter tuning was carried out using RandomizedSearchCV. This approach is especially useful when time and computational resources are limited, since it provides a more effective substitute for exhaustive search techniques such as GridSearchCV. In order for RandomizedSearchCV to function, a predetermined number of hyperparameter combinations are randomly sampled from a predefined grid or distribution. In comparison, GridSearchCV analyses each and every possible combination of hyperparameters in the given grid in a methodical manner. RandomizedSearchCV is ideally suited for large datasets or models with numerous hyperparameters because it strikes a balance between thoroughness and efficiency by keeping the number of combinations to a manageable level.

Then, each model's hyperparameter space was carefully defined to examine a variety of possible values that might enhance the model's performance. Particular hyperparameters for every model were found, and a grid of values was created for RandomizedSearchCV to investigate:

Random Forest
Number of Trees (n_estimators): The number of decision trees in the ensemble was varied across 50, 100, and 200. By lowering variance, adding more trees usually improves model performance, but it also increases computing requirements.

Max Depth (max_depth): The maximum depth of each tree was set to either 10, 20, or left unrestricted (None). Although deeper trees can capture more complex patterns, if they are too deep, overfitting could happen.

Minimum Samples Split (min_samples_split): This parameter, which dictates the minimum number of samples required to split an internal node, was tested at 2, 5, and 10. Higher values, which reduce the tree's complexity, can aid in preventing overfitting.

Minimum Samples Leaf (min_samples_leaf): Values of 1, 2, and 4 were used to investigate the minimum number of samples needed at a leaf node; larger values may result in smoother models.

KNN (K-Nearest Neighbors):
Number of Neighbors (n_neighbors): The model was tested with 3, 5, and 7 neighbors. The decision boundary's smoothness is determined by its number of neighbors; more complex boundaries result from having fewer neighbors.

Weights: Two weighting schemes, 'uniform' and 'distance', were evaluated. While 'distance' gives closer neighbours more sway, 'uniform' gives all neighbours equal weight.

Algorithm**:** 'Auto', 'ball_tree', 'kd_tree', and 'brute' were among the algorithms in the search space that were used to determine the most effective way to find nearest neighbours under various dataset conditions.

Decision Tree:
Max Depth (max_depth): To balance overfitting and model complexity, the maximum depth was adjusted between None, 10, and 20, much like in Random Forest.

Minimum Samples Split (min_samples_split): The number of samples that must exist before a node can be split was tested with values of 2, 5, and 10.

Minimum Samples Leaf (min_samples_leaf): The granularity of the tree's terminal nodes was affected by varying the minimum samples at leaf nodes between 1, 2, and 4.

Gradient Boosting Machines (GBM):
Number of Trees (n_estimators): The number of boosting stages to be run was explored with 50, 100, and 200 trees. Longer training sessions can result from more stages, but improved performance is also possible.

Learning Rate (learning_rate): Learning rates of 0.01, 0.1, and 0.2 were tested to determine the step size at each iteration. Although a lower rate typically necessitates more iterations, it can lead to improved generalisation.

Max Depth (max_depth): The depth of individual trees was adjusted in steps of 3, 5, and 7, which had an impact on the model's ability to represent feature interactions.

XGBoost:
Number of Trees (n_estimators): To balance computational efficiency and model accuracy, the number of trees was set to 50, 100, and 200, much like in gradient boosting.

Learning Rate (learning_rate): The learning rate, which was tested with values of 0.01, 0.1, and 0.2, was crucial in determining how quickly the model converged.

Max Depth (max_depth): In order to enable the model to handle different levels of data complexity, the maximum depth for trees was investigated at levels of 3, 5, and 7.

By capturing a broad variety of possible model configurations, these hyperparameter grids allowed RandomizedSearchCV to determine the optimal set of hyperparameters for every model while weighing the trade-off between computational efficiency and accuracy. By guaranteeing a comprehensive investigation of the hyperparameter space, the defined ranges raised the possibility of discovering the ideal model configuration [18].

The performance of each model was thoroughly assessed using 5-fold cross-validation for every combination of hyperparameters. This procedure began with splitting the dataset into five equal portions, or "folds." It was then made sure that every segment of the data had an opportunity to be used as the validation set by training the model on four of these folds and validating it on the fifth fold. To guarantee a thorough evaluation of the model's performance, this process was carried out five times, using a different fold as the validation set each time around. An average of the results was determined for each of the five folds using critical performance metrics like Mean Squared Error (MSE) and Mean Absolute Error (MAE). This averaging took into account the variability in the data and decreased the chance of overfitting, resulting in a reliable estimate of the model's overall performance for the specified set of hyperparameters.

RandomizedSearchCV was used to refine the hyperparameters over ten iterations after the cross-validation procedure and every iteration used a random selection of new hyperparameters from the pre-established grid [18]. Next, using the previously mentioned 5-fold cross-validation method, the model was trained and validated using the chosen hyperparameters [18]. Performance measures like mean square error (MSE) and mean average error (MAE) were carefully documented for every iteration, enabling a thorough comparison between various hyperparameter combinations. After every iteration, RandomizedSearchCV determined which hyperparameter combination produced the best results, optimising the model according to the lowest recorded MAE or MSE. Significant benefits came with this approach: it was computationally efficient, requiring less time and resources than exhaustive grid search methods; furthermore its versatility across various models was attributed to its flexibility in handling diverse hyperparameter spaces. Additionally, by randomly navigating the hyperparameter space, RandomizedSearchCV might find useful combinations that a more rigorous search might have missed, improving the overall performance of the model.

However, It is crucial to note that the optimization process becomes more random when RandomizedSearchCV is used. Due to this randomness, the model's performance may slightly differ between runs because the particular set of hyperparameters chosen will depend on the random seed used in the search. As a result, different instances may have different optimal hyperparameters than others, which could have an impact on the consistency of the model's performance metrics, including Mean Squared Error (MSE) and Mean Absolute Error (MAE). In order to counteract this impact, the tuning procedure was repeated several times, averaging the outcomes to guarantee the final model selection was robust.

Model Evaluation and Selection

After hyperparameter tuning, the models were assessed using two common metrics for regression tasks: Mean Squared Error (MSE) and Mean Absolute Error (MAE). These metrics offered information about the precision and dependability of each model's predictions. Then we summarizes the optimal hyperparameters found for each model, along with their corresponding MSE and MAE values in a table (refer to Appendix, Figure 9). With the lowest Mean Squared Error (MSE) and a competitive Mean Absolute Error (MAE), the Gradient Boosting model was the top performer according to the evaluation metrics. This model is the best option for ultimate implementation since it constantly produced accurate predictions in all scenarios.

Final Model Implementation

Following the comprehensive evaluation, the Gradient Boosting model was chosen for final implementation due to its superior performance, as evidenced by its lowest Mean Squared Error (MSE) and competitive Mean Absolute Error (MAE). Using RandomizedSearchCV and rigorous cross-validation to find the ideal hyperparameters, the model was trained on the complete pre-processed dataset. Because of its thorough training, the model was able to identify all of the complex patterns in the data and predict procurement prices with accuracy. Through the provision of actionable insights and the identification of potential cost-saving opportunities, the implementation of this model in a production environment holds significant potential to improve decision-making processes, particularly in the areas of procurement and supply chain management.

Alert System Configuration setup

To improve cost efficiency and optimise procurement processes, we developed and implemented a predictive model aimed at identifying potential savings opportunities. This methodology describes the steps we took to incorporate this model into the configuration of an alert system so that overpayment could be detected in real time and timely corrective actions could be made.

We began by defined precise thresholds that distinguish between different levels of saving opportunities in order to quantify and classify potential savings. These cut-off points were established by calculating the percentage that separates an item's actual unit price from the price that our model predicted: High Saving Potential: When the real price is more than 5% higher than the estimated price (marked in red). When the price is more than 3% but less than 5% above the expected price, there is a medium saving potential (highlighted in yellow). Low Saving Potential: indicated by a green flag when the price is 0.5% to 3% higher than expected. Prices differing by 0.5% or less from the predicted value were considered to have no saving potential and were flagged as None. These thresholds were essential for prioritizing alerts and ensuring that significant cost saving opportunities were promptly addressed.

In order to operationalize the predictive model, we created a set of functions that collectively produce valuable insights. The 'generate_flags' function uses the thresholds to determine each item's potential savings and then assigns a flag to it. The flag indicates the amount of potential savings by classifying the item as red, yellow, green, or none. Procurement teams can rapidly determine which items need to be addressed right away because of to this categorisation. The 'generate_alerts' function, the main component of the alert system, compares the current procurement price to the projected price from the model to determine the potential savings for each item. Only the items where the current price exceeds the projected price, indicating a possible overpayment, are filtered out and alerts are generated. The appropriate flag (red, yellow, or green) is then assigned based on the size of the savings, which is crucial for prioritisation. The 'check_item_savings' function compiles the system-generated alerts and displays them in an organised manner. Procurement managers can review the items that have been flagged, comprehend the possible savings, and adjust their actions accordingly. The function is made to concentrate on particular goods and businesses, allowing for focused analysis and decision-making.

We integrated the predictive model into the alert system after it was developed and validated so that it could be used as a standard for determining possible savings. Every item's reference price was derived from the model's predictions and compared to the procurement price as of right now. By comparing the two, the system was able to determine when an item was being bought for a price that was noticeably higher than its expected market value and send out an alert. For multiple reasons, the predictive model's integration was essential. Initially, it guaranteed accuracy by offering a data-driven foundation for figuring out fair market prices, making sure alerts were grounded in solid statistical forecasts rather than arbitrary cut-off points. Secondly, it improved efficiency by eliminating the need for manual price checks, automating the detection of possible overpayments, and freeing up the procurement team to concentrate on high-impact areas. Thirdly, it encouraged proactivity by facilitating early detection of cost-saving opportunities and real-time monitoring, which enabled the organisation to make necessary adjustments before unwarranted expenses mounted. This experimentation addressed important areas like cost optimisation, decision support, data-driven insights, and scalability and was required to validate the model's efficacy and integration into the alert system. An informed, scalable, and financially aligned approach to procurement could replace the organization's current intuition-based practice by methodically examining price deviations and potential savings.

5. RESULTS

A focused analysis was carried out using invoice records from the previous two months in order to evaluate the efficacy of the developed alert system in actual procurement scenarios. By contrasting actual purchase prices with those predicted by our predictive model, the main goal of this analysis was to assess the system's capacity to spot possible cost-saving opportunities. The assessment focused on current and pertinent data in order to assess how well the system could improve procurement procedures by sending out precise and timely alerts.

The alert system was used in a procurement scenario for the purchase of " CEBOLA " and " TOMATE LONGA VIDA" in order to demonstrate its functionality. Based on recent purchasing behaviour, the procurement team intended to purchase these items in particular quantities. The most recent two months' worth of invoice data provided the following information: 10 unit of CEBOLA and 15 units of TOMATE LONGA VIDA. These inputs were received by the alert system and determined if these prices agreed with the estimated fair market prices produced by our predictive model. It examined the supplied prices after obtaining the input data by contrasting them with the model's anticipated prices, which were established by past data and market patterns. After receiving the input data, the alert system processed the prices by examining differences between the expected and actual values. These differences were categorized by the system based on pre-established thresholds intended to measure possible savings. Items were designated as having "High Saving Potential" by the system when the actual price was higher than the predicted price by more than 5%, "Medium Saving Potential" when the difference in price was between 3% and 5%, "Low Saving Potential" when the difference in price was between 0.5% and 3%, and "No Saving Potential" when the difference in price was negligible. The system computed the potential savings if the items were purchased at the recommended prices by identifying potential differences between the actual and predicted prices. Below screenshot of the alert for the above two item shown.

```python
# Testing the results
item_quantities = {
    'CEBOLA': 10,
    'TOMATE LONGA VIDA': 15
}
company_id = '1015'
check_item_savings(company_id, item_quantities, filtered_data, overall_best_model,features_for_training, only_red_alerts=False)
```

```
Total potential savings for item CEBOLA and company 1015: $6.33 with quantity 10
Alert: NOBORU HORTIFRUTI EIRELI - ME selling CEBOLA to 1015 at $6.30, which is higher than the predicted price of $5.98. Potential savings: $3.16 (5.29%) Flag: red
   Predicted price: $5.98
   Average price from other companies (below predicted price): $5.65
Alert: NOBORU HORTIFRUTI EIRELI - ME selling CEBOLA to 1015 at $6.30, which is higher than the predicted price of $5.98. Potential savings: $3.16 (5.29%) Flag: red
   Predicted price: $5.98
   Average price from other companies (below predicted price): $5.65
No red alerts found for item TOMATE LONGA VIDA and company 1015.
```

Through data-driven analysis and real-time alerts, the alert system's implementation proved its ability to improve procurement decision-making. Procurement teams can minimize unnecessary expenses by promptly taking corrective action when the system correctly identifies overpayment instances. The present case study demonstrates the pragmatic advantages of incorporating predictive models into procurement workflows. It provides a scalable approach to cost optimization and overall efficiency enhancement.

6. LIMITATIONS

Even though the project's limitations have no impacts on its overall value, they do point out areas where future improvements could be made to increase the predictive model and alert system's robustness and applicability. One major drawback is the over-reliance on historical data. The predictability of the model relies on the availability and quality of this data. The model's predictions might be less accurate if the data is inaccurate, out-of-date, or lacks certain information. Furthermore, the model makes the assumption that past performance is indicative of the state of the market today. Predictions may be less accurate as a result of the model's inability to adapt quickly enough to the market.

Another challenge lies in the model’s ability to generalization. Due to the fact that the alert system and model were developed and tested using a particular set of products and suppliers, their applicability to new products or suppliers that were not included in the initial training dataset may be limited. Because of this dependence on particular data, there is a greater chance of overfitting, a phenomenon in which a model performs well on training data but is unable to generalise to new data, which can result in erroneous price predictions and ineffective alerts.

External market factors further complicate the model accuracy. Sudden market fluctuations brought on by occurrences like economic crises, supply chain interruptions, or other outside factors might not be fully taken into account by the model. These occurrences might make the model's forecasts less accurate, which could result in false alarms or lost savings opportunities. Furthermore, the model ignores long-term contracts and the subtleties of supplier negotiations, both of which have a big impact on procurement costs. As a result, in cases where price discrepancies result from contractual clauses rather than actual overpayment, alerts might be produced.

Another notable project limitations include system scalability and maintenance, as well as user adoption and interpretation. The computational demands of the alert system and model increase with the number of items, suppliers, and transactions; this could have an impact on scalability and responsiveness. In order to maintain accuracy in dynamic markets, the model also needs to be periodically retrained and validated. This is a process that can be resource-intensive and requires careful management. The efficacy of the system is contingent upon user trust; should procurement teams have doubts regarding the model's predictions or perceive the alerts as excessively conservative or aggressive, the system's impact may be curtailed by their partial adoption.

7. CONCLUSION

In summary, the objective of this study was to apply predictive analytics to find possible cost-saving measures in order to improve the efficacy of procurement procedures. Several important project milestones were successfully reached, starting with the thorough data preparation that guaranteed the reliability and correctness of the procurement data used in the modeling. This fundamental stage reduced the possibility of biases or errors that could skew the model's results and allowed the creation of a dataset that accurately represented the procurement environment, which was essential in building a strong foundation for the predictive analysis.

After the data preparation stage, a comprehensive analysis of different predictive models was carried out. Gradient Boosting was found to be the most effective option among them, exhibiting impressive predictive accuracy. When compared to the other models examined, it had the lowest Mean Squared Error (MSE) and a competitive Mean Absolute Error (MAE). Gradient Boosting is the most accurate model for estimating procurement costs because of its capacity to capture the intricate relationships present in the procurement data, as demonstrated by these metrics.

The impact of the project was enhanced even further by the creation and integration of an alert system. This system efficiently converted the insights from the predictive model into actionable alerts for procurement teams by identifying high-cost transactions that offered substantial opportunities for savings and they can concentrate their efforts on the most significant areas, which resulted in significant cost reductions, thanks to the ability to prioritize transactions based on potential savings. The procurement process was deemed more efficient overall because of the system's real-time alerts, which made sure that any potential overpayments could be promptly addressed.

The project's findings were very impressive. When it comes to accurately estimating procurement costs and identifying significant savings across a wide range of products and suppliers, the Gradient Boosting model consistently outperformed other models. The alert system enabled procurement teams to make well-informed decisions that directly aided in cost optimization by giving them access to concise and useful insights. Therefore, decision-making procedures and overall procurement efficiency were significantly improved by the incorporation of predictive insights into procurement strategies. This proved the practical financial and operational advantages of deploying data-driven alerts in addition to validating the model's efficacy.

To sum up, the project has successfully illustrated how predictive analytics may transform the procurement process. The initiative has greatly improved procurement practices by combining accurate modeling techniques with a strong alert system, providing a potent tool for cost control and strategic decision-making. The effective execution of this strategy has established a solid basis for upcoming cost-cutting initiatives, placing the company in a position to consistently enhance its procurement procedures and attain increased financial efficacy. This study offers a convincing illustration of how data-driven approaches can transform traditional procurement tactics, offering long-term benefits and opening the door for more advancements in the industry.

8. FUTURE SCOPE

This project's future offers a number of exciting possibilities that could greatly improve its efficacy and applicability in the near and long terms. Adding real-time data to the predictive model is one of the first things to think about. As things stand, the model's capacity to react to abrupt changes in the market or unforeseen shifts in the economy is limited by its dependence on historical data. Incorporating real-time market data, supply chain details, and economic indicators could enhance the model's predictive power and timeliness. Additionally, by ensuring that procurement decisions are based on the most recent information available, this would make the system more responsive to changes in the market.

Increasing the variety of products and suppliers in the model's training dataset could be a focus in addition to real-time data integration. This would assist with fixing the current generalization limitation of the model. A more varied dataset would lower the chance of overfitting and increase the model's general relevance by enabling it to handle new products or suppliers that weren't included in the original dataset. Incorporating external market factors such as commodity prices and macroeconomic trends into the model could also help account for variables that affect procurement costs but are not taken into account at this time. This would improve the model's prediction accuracy and strengthen the alert system's ability to identify possible savings.

Going forward, increasing user adoption and system trust may also be important areas of focus. The alert system could be made more relevant and user-friendly by allowing procurement teams to modify thresholds according to their unique requirements. Furthermore, creating a feedback loop where users can offer feedback on the alerts' usefulness and accuracy could aid in improving the model's accuracy and alignment with the organization's objectives and operational realities.

Finally, users may gain a great deal from improving the system's reporting and visualization features. Procurement teams could take proactive steps and make better decisions if they were able to interpret the data and insights produced by the model more easily through the use of interactive visualizations and intuitive dashboards.

In conclusion, there is plenty of potential for improvement in terms of accuracy, scalability, and user adoption as this project continues to be developed. The project can become a more robust and versatile tool by emphasizing real-time data integration, growing the training dataset, adding external market factors, and improving user interaction. These developments would improve procurement procedures while also offering insightful strategic information that could lead to long-term cost reductions and increased productivity throughout the company.

9. DECLARATIONS

I, Ashutosh Kumar Sonu, hereby declare that, with a handful of instances where it is explicitly stated and properly cited, this thesis is a result of my original work that I completed on my own. I certify that this submission complies with good academic practices and that I am fully aware of the University of Exeter's policy on plagiarism. Furthermore, ethical guidelines were followed in the conduct of this study. There were no experiments involving humans or animals, and no personal information about humans was processed. Since there are no activities related to security or safety that are crucial to the study, all possible ethical issues have been resolved in accordance with university policies.

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11. APPENDIX

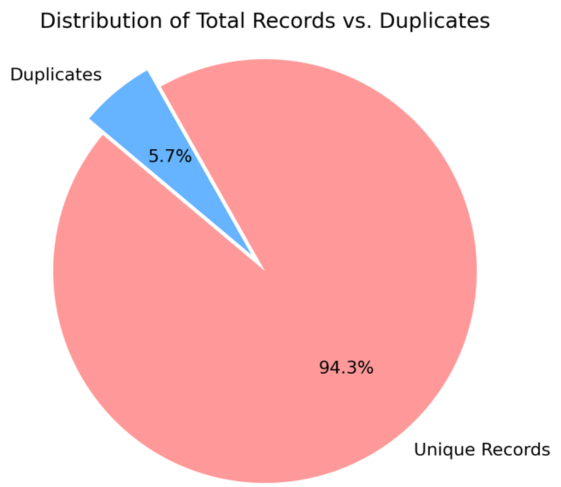

Figure1: Distribution of duplicates. Vs total records

Figure2 : Highly Right skewed column

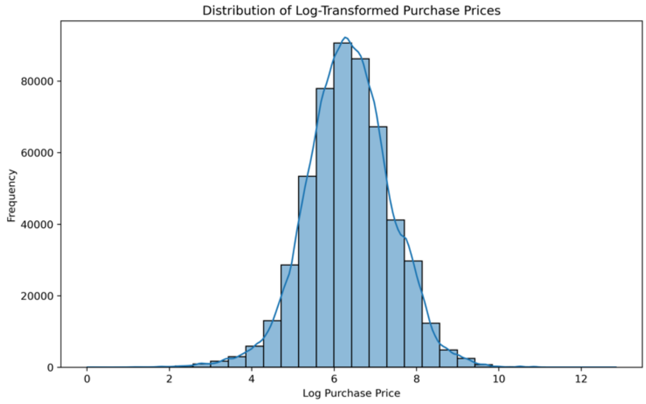

Figure3 : Log transformed column, resembling normal distribution

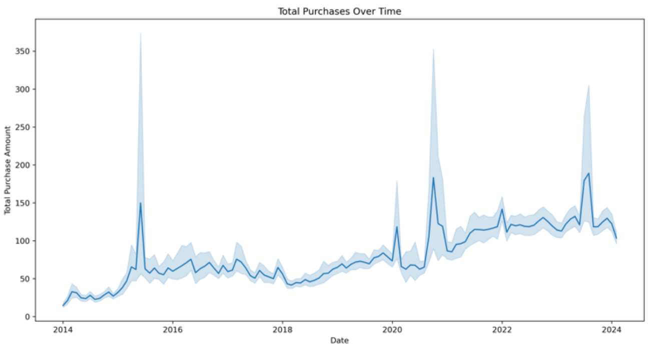

Figure 4 : Purchase trends over time

Figure 5: Total purchase over time by company

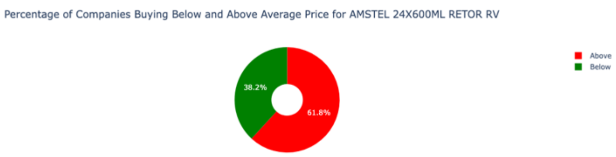

Figure 6: Distribution of companies purchasing above and below average unit prices

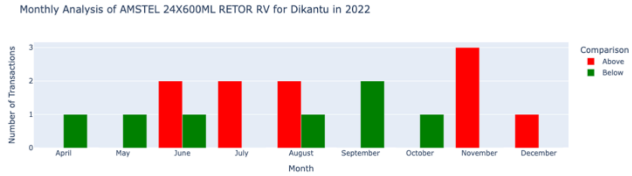

Figure 7 : Focused analysis on companies purchasing above and below prices.

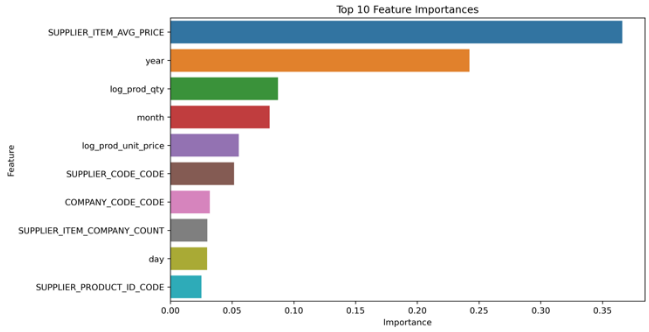

Figure 8: Top 10 feature contribution

Model	Best Parameters	MSE	MAE
RandomForest	{'n_estimators': 100, 'min_samples_split': 2, 'min_samples_leaf': 1, 'max_depth': 10}	116691.62	1.56175154
KNeighbors	{'weights': 'distance', 'n_neighbors': 3, 'algorithm': 'kd_tree'}	310945.155	6.03549583
DecisionTree	{'min_samples_split': 2, 'min_samples_leaf': 2, 'max_depth': 10}	218507.773	2.31723336
GradientBoosting	{'n_estimators': 200, 'max_depth': 3, 'learning_rate': 0.1}	86227.0427	1.85652852
XGB	{'n_estimators': 200, 'max_depth': 3, 'learning_rate': 0.1}	87191.6155	7.37483321

Figure 9: Evaluation Matrix