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Leveraging Artificial Intelligence and Machine Learning for Predictive Bid Analysis in Supply Chain Management: A Data-Driven Approach to Optimize Procurement Strategies

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Within the context of supply chain management, there has been increased research interest in leveraging the power of data analytics to provide decision support for more effective procurement strategies. This study focuses on how different dimensions of data analytics, driven by advancements in machine learning, can be more systematically incorporated in the context of a larger research framework to understand why suppliers behave the way they do, and ultimately guide procurement strategies in both strategic and operational sourcing. The development of predictive models and analysis includes the use of predictive analytics to provide valuable insights into expected suppliers' bidding behavior from an action-oriented context by being provided with strategic information in the pre-bid stage and a business setting that could be easily explained and interpret values of the model.
The dependable bid model was built based on well-thought-out hypotheses and causal pathways to predict suppliers' behaviors using artificial intelligence, machine learning, multiple linear regression, decision trees, and adaptive neuro-fuzzy inference system algorithms. The data to build the models were collected from real strategic and operational sourcing processes for various medium- to large-sized international suppliers. The models were validated and tested using different out-of-sample testing methods. The models' results contribute to bidding practice by detecting a number of opportunities for practitioners involved in supplier evaluation to reach out for alternative methods and can empirically capture structured or semistructured data attributes to meet the task accuracy. Its optimization capabilities and its ability to relate the configured composing prediction elements to the results are demonstrated with a real-life bidding case. Its combined benefits and use in a procurement strategy consisting of formal and informal auctions in a portfolio setting were the key to attaining significant cost savings. Its model construction guide and the measures of model interpretability are expected to create new opportunities for the developer of the organization's decision support systems. Its modular prediction system anticipates the achievement of a high cost savings rate while maintaining a dual workload with consideration of the annual average number of contracts in different direct sourcing practices. Its ability to adjust the costs of the business rules involved aims to predict significant cost variance of the method in dollars from the predicted total dollar volume bought.

Keywords: Predictive Bid Analysis,Artificial Intelligence (AI),Machine Learning

(ML),Supply Chain Management (SCM),Procurement Optimization, Data-Driven Procurement, Bid Forecasting,AI-Driven Supply Chain,Supplier Selection,Bid Evaluation Algorithms,Procurement Strategy,Predictive Analytics,Cost Prediction Models,Procurement Decision Support,Supply Chain Optimization.

1. Introduction

The function of procurement is to purchase goods or services that are required by the enterprise. Predominantly, this process involves issuing RFPs, consolidating bids, and awarding business to suppliers for delivering goods and services as per the agreed-upon terms and conditions. However, the traditional procurement process is time-consuming, and the "usual" metrics are not always reflective of the critical factors for evaluating and selecting the right supplier. The RFP provides some standard information about the potential supplier, but many questions are complex or subjective and are not all answered thoroughly, leading to potential inaccuracies. To mitigate the risks associated with the existing purchasing process, it is essential to leverage recent technological advancements in data analytics, predictive analysis, artificial intelligence, and machine learning to benchmark the supplier's performance based on information captured from the RFP and historical data.

The motivation for our research is derived from a real case. A large utility provides electricity to 2.4 million customers in northern Alberta and needed to replace approximately 36,000 of its current 48,000 electrical power meters with distribution automation meters. The advanced metering infrastructure project involved designing, supplying, installing, and commissioning the technology to collect consumption data from these new meters for the purpose of billing customers, monitoring system performance, managing load demand, and managing customers' electricity usage. The company issued an RFP to enhance meter capability and detailed requirements for the design, functionality, and operation of the meters and associated communication network. The bid selection process included formal score evaluations, interviews, presentations, and solution demonstrations. The RFP scorecard comprised 50% for functionality, 20% for timeline and total cost, 20% for quality of service, and 10% for the contractual price and warranty. The responses from the qualified parties were subjectively analyzed using the above parameters, and the contract was awarded to a vendor. The procurement process seemed low risk simply because of the clear and simple award criteria. It was believed that bidding companies would select vendors who had already established reputations in this type of work and would provide economically sensible solutions.

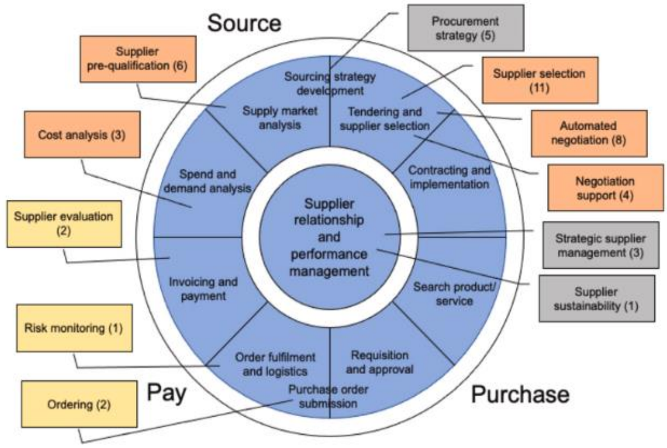

Fig 1: Artificial intelligence and machine learning in purchasing and supply management

1.1. Background and Significance

With globalization on the rise, businesses rely heavily on raw materials, goods, and commodities purchased from all corners of the world. The cost of the supply chain has become a major part of total sales, while the potential for supply chain failure can have significant impacts on procurement processes. To mitigate these risks, managers often establish relationships and contracts with a diverse array of suppliers that allow for adjustments based on current economic conditions. Understanding and predicting price movements are key components of supply chain management, particularly for enterprises procuring large amounts of materials. The goal is to obtain the highest quality materials at the lowest possible price. The use of artificial intelligence and machine learning has significantly improved prediction accuracy across a range of applications. Modern procurement departments can leverage data-driven predictive tools to anticipate future price movements and adjust procurement strategies to reduce total cost of ownership.

An opportunity exists to leverage recent advancements in artificial intelligence and machine learning to develop tools to assist procurement departments in making strategic business decisions. These decisions range from whether to 'build' or 'buy' to which supplier to choose for a given sourcing event. The recent confluence of big data and powerful learning models is what sets the stage for the predictive bid analysis problem explored here. Although we focus on the procurement of commodities for use in manufacturing enterprises, it is worth noting that the size and diversity of the data are similar to other applications. Familiar examples involve the procurement of raw materials in other realms, where large international volumes and dozens of running contracts feed into a complicated and opaque acquisition process. The case of commodity procurement for manufacturing is a classic example of a 'big data splash' problem. It is large, ill-structured, and the model itself is incorporated directly into human decision-making.

Equ 1: Predictive Model for Bid Selection Using Machine Learning

$$P(\mathrm{Win}_i|\mathbf{X}_i) = \frac{1}{1 + e^{-f(\mathbf{X}_i)}}$$

Where:

- $f(\mathbf{X}_i)$ is the function learned by the machine learning algorithm.
- The output $P(\mathrm{Win}_i)$ gives the likelihood of bid B_i winning.

For **logistic regression**, the function $f(\mathbf{X}_i)$ is typically linear:

$$f(\mathbf{X}_i) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

1.2. Research Objectives

This research investigates a novel approach to leveraging artificial intelligence and machine learning tools to provide quantitative evidence of the impacts of supply chain management strategies on contractual pricing offers requested in public procurement processes, in order to increase the effectiveness and efficiency of procurement decisions. The specific objectives of the research focus on the introduction of a set of applications to propose a predictive tool that can extract best practices and successful strategies from the perspective of the buyer of goods or services addressed in the procurement through the support of negotiations focusing on the critical points highlighted by the tool, and propose the most effective strategies and practices that can be adopted to achieve successful results in the contemporary perspectives of sustainable procurement. A further result of the research consists of the introduction of a novel framework characterized by the analysis of unusual features of the public sector, such as the commonalities associated with purchase portfolios and part of the negotiations before the carefully described peculiarities that the approach introduces for the monitoring of various types of negotiations over time to verify the associated possible benefits in terms of effects on transaction costs, and thereby assess the effectiveness of the knowledge-building of the artificial intelligence tool and guide the most appropriate choice of interventions that public buyers can manage to improve practice in line with the dynamics of governance associated with the organization of a decentralized public authority.

2. Literature Review

In these days of digital transformation, companies are looking for ways to optimize their resources, improve their supply chain, and reduce costs, constantly demanding greater cooperation, trust, and transparency throughout the supply chain. In the specific case of the procurement function within the supply chain, organizations are trying to move from a tactical and transactional role, mainly focused on cost reduction, to a strategic function that contributes to business growth and innovation. Currently, the main objectives of a company's procurement strategy are to reduce business expenses, obtain better payment terms, and improve relationships with trusted and reliable suppliers, to have suppliers that offer better quality and innovate, and to reduce dependence. The purpose of this research is to present a framework that enables individuals and organizations within a supply chain, both large and small, to predict the prices or total costs of products or items in a manner that improves transparency among trading partners. In addition, this research is designed to present a practical and scalable model that utilizes AI and ML for the exploration of large and complex datasets made available by emerging platforms and custom data of trading partners. The proposed model embraces the flexibility of the platforms and is capable of predicting transaction prices based on different modeling, cost/price capture techniques, and data of trading partners of different depth and attributes. The assumption underlying the development of this Technology Business Model is that web-based platforms can be cost-effectively multicast using traditional and modern technologies. These technologies could provide the necessary storage, communication, and analytics in order to share AI and ML models with weaker individuals connected to the web. Moreover, this proposed platform could improve data quality, reduce detection, and increase transparency in trading relations. The ultimate goal is to support forecasting and the implementation of rule-based algorithmic trading strategies that could foresee prices or costs through the use of several AI and ML prediction models suitable for various item classes.

2.1. Artificial Intelligence and Machine Learning in Supply Chain Management

In our manuscript, we focus on novel ways to predict the outcome of the RFP/RFQ process by employing a data-driven approach using artificial intelligence (AI) and machine learning (ML) models. Animated by such an AI/ML procurement, companies can enhance their internal capabilities to better understand the uncertainty of the future bidding process, generating personalized responses and winning strategies. Thus, the main scientific core of our study is to identify a data-empirically supported AI/ML predictive model, encompassing either one or an ensemble of several ML algorithms to maximize winning chances if the response is eventually submitted. As of today, AI intelligence has gained popularity. In contrast to traditional business intelligence tools, in AI the ultimate decision-making remains always with the domain expert, without any machine-based constraints. In this section, we first summarize the existing literature regarding AI and ML in the context of supply chains, then provide a comprehensive classification as seen in the literature.

2.2 Artificial Intelligence and Machine Learning in Supply Chain Management It is evident that the majority of supply chains are complex and consist of various nodes, each communicating with transactions and transporting physical goods. To make effective decisions, one has to be in possession of end-to-end supply chain data, namely from customers to suppliers. Along the sourcing supply chain perspective, it has been known for quite some time that once the technology enablers of the industrial internet of things and AI/ML are used at any spot, the real-time data produced will provide valuable insights. The application of AI/ML skills can provide end-to-end supply chain visibility which can constitute a valuable strategic weapon. Note that this visibility is provided not only for the raw transportation and manufacturing data, as in the past, but for the entire process.

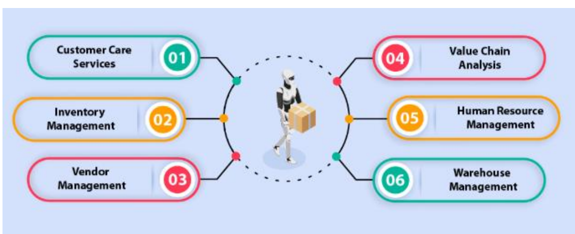

Fig 2: Artificial Intelligence In Supply Chain

2.3. Predictive Bid Analysis

Thanks to big data, it has become possible to track all bids or trading actions and responses. Thus, such vast amounts of data allow predicting future performance based on data patterns and trading responses thanks to AI and ML. Data-driven insights that learn from trading behaviors generate custom KPIs for categories, identify market trends and outliers, and address competition besides demand and spending avoidance. By doing so, these demand-side insights address supply chain challenges that so far are not addressed properly.

Optimizing the terms and conditions of RFPs and RFQs based on big data and advanced analytics generates substantial savings for buyers. Accurate performance prediction enables sounder go/no-go decisions in eSourcing, enabling enterprises to focus on those products and suppliers that add the most value, thus enabling more efficient decision-making and increasing the value of investigation. Analysis of anonymized bid rejection rates provides feedback to improve supplier relationships by feeding suppliers information that helps them to improve, so the eSourcing processes become a win-win process. Upon the completion of negotiations and the customized terms and conditions being inducted into the contract module, the predictive insights are tracked to ensure the realization of savings.

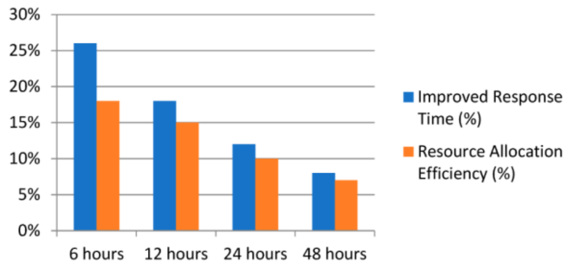

Fig 3: Predictive Analytics and Machine Learning for Real-Time Supply Chain Risk Mitigation and Agility

2.4. Optimization in Procurement Strategies

To optimize the procurement budget, companies can decide to apply different procurement strategies to create competition among suppliers, control suppliers' excess profits, minimize total costs, and satisfy various collection requirements. A sourcing strategy is typically based on two factors: requirements that can be fulfilled by different types of suppliers and market conditions. This text focuses on four typical market conditions with different levels of intrinsic risks and different overall budget levels. The feasible sourcing strategies include single sourcing, dual sourcing, outsourcing, and flexible sourcing. In the flexible sourcing strategy, firms keep a certain proportion of production in-house and search for a flexible sourcing supplier to cooperate with. This idea is consistent with many traditional research results in close markets and collaborative supply chain networks. Firms can decide to implement a flexible sourcing strategy composed of both internal procurement and flexible sourcing procurement with an internal ratio of n and a flexible sourcing ratio of 1 - n. By comparing the total costs associated with different procurement strategies, firms can make decisions on the optimal procurement strategies.

There are several procurement strategies available for an enterprise in the production outsourcing stage. In practical use, the single sourcing, dual sourcing, and flexible strategies are widely used. When making procurement decisions, enterprises make decisions based on the total costs. Enterprises could choose potential suppliers from different countries, and these may be unstable and risky. Once an enterprise selects a supplier, it may lose its flexibility in sourcing strategy. This model employs randomness in the exogenous parameters and uses the binomial model as a mean-variance criterion for a flexible sourcing supply chain, which serves to provide a comprehensive target forecast for the exogenous parameters.

3. Methodology

3.1. Predictive modeling To investigate and evaluate the likelihood that a given variable is influential in the determined group of bidders' strategies, a battery of machine learning techniques will be utilized. Techniques like support vector machines, random forests, and gradient boosting will be applied in a preliminary analysis to assess the top variables. A support vector machine is used for high-dimensional problems and is effective when the sample size is relatively small, especially for the training time of standard classifiers. The random forests technique will be used to represent the most effective classification and regression tool if a linear relationship does not fit the purpose. The combination of the procedures applied will be used and is also not easily affected by other multicollinearity problems.

3.2. Data To test our hypothesis, we have utilized the dataset. From this dataset, we have extracted information on different models like year, make, and model data. Nevertheless, the dependent variables will mostly be based here on quantitative measures of supplier behavior, growth, profitability, and the intermarket attribution of the subjective and objective data will be processed to verify the suppliers' relationship with their past bid patterns.

3.3. Data Collection and Preprocessing

In order to study the influence of these factors on bid selection, we designed and generated a dataset by capturing unionized tender project information. Our company offered big data mining services based on public data to provide integrity analysis, business transaction risk control, and credit support for enterprises. The public data can only be collected through special authentication channels, and the data collection does not involve privacy issues. After detailed discussions, it was found that the main data affecting the successful bid of the procurement project could be obtained, such as subcontract volume, subcontractor, consortium main body, cash deposit, and so on. Finally, we captured the needed data after carefully setting the corresponding sampling frequency. Our final data involve a total of 70,716 tender projects with successful tenders and 2,179 parameters with 95% accuracy. The tendering process and results will be made public after the projects have been completed. This information can help generate a historically rich dataset for analysis.

The parameters include six aspects: ancillary service characteristics information, system card, financial data, personnel demographic data, corporate performance, and subcontractor information. Ancillary service characteristics information describes the type, section, and service content of the ancillary service, service requirement of site survey needed or not, valid period of the quotation, and qualification and account settings before quotation. The system card includes the consortium plan, the responsible person in the consortium, supplementary contract terms, participant notice, salary settlement deadline, expenses payment deadline, and so on. The financial data derived from a comprehensive review of the consortium member, general tax number, auditing department, approving bank, and payment data. The personnel demographic data include employee location, contact person, ID card, military officer, traffic location, place of origin, quickest road crossing time to the work site, and leasing the most timely delivery. Corporate performance is defined as the company's previous administration, the portfolio project completed by the employee, the director's performance statement, legal certificate, regional payment situation of the project portfolio, and the legal vendor's main body. The subcontractor information includes the procurement transaction amount, purchase amount, procurement platform discount, past procurement experience, bidding platform, and payment method. With the exception of the system card, part of the bid was artificially marked by experts to generate the parameters. All the parameters were preprocessed before analyzing the parameters.

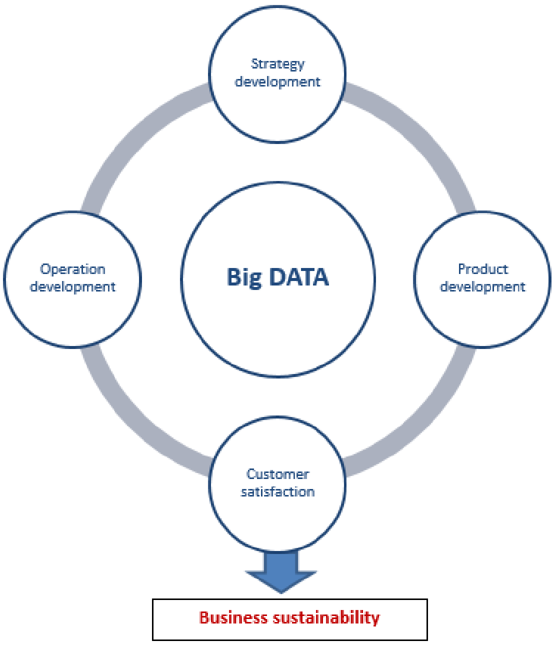

Fig 3: Big data Process

3.4. Model Development and Training

The first step in model development is to integrate an artificial intelligence technology such as machine learning with human domain knowledge, other decision technologies, and especially a business context. In this model, we use predictive machine learning as a tool because predictive modeling alone does not address the procurement strategic part of the problem to be solved. Predictive model parameters need careful specification in the actual applications. On the other hand, as is typically the case in random forests, such as the number of trees to grow, the variable names, variable transformations, variable ordering, and variable missing value processing. These parameters have no standard analytical solution but rather involve research, trial and error, guess and check, education, business insight, and best guess, all on an ongoing unified basis.

The present models are built using the popular classification and regression tree method, in its related form of random forests. In this application, random forests methods use all the predictors the same way, and we have not embedded the model in a larger optimization framework. Using the decision tables, we found the presence of much approximate logical interaction structure, and in the next stage, we proceed to adjust to the fact for all subsequent model development. The specific tool used was R with the random forest package, which has claimed the state of the art in commercial predictive modeling because of its ability to handle complex data structures and its out-of-the-box performance. In particular, the package proved to be extremely stable with random forests over varying data, and it provides simple internal feature information and strength information in choosing the primary driver of a finding. Because they can be based on a relatively non judgmental feature importance metric measure with intuitive interpretation, these nonparametric methods pinpoint procurement predictors in ways that are often more reliable and always more unbiased than the commitment methods of highly skilled procurement professionals.

3.5. Evaluation Metrics

Profit maximization is an important objective in bid analysis in the construction supply chain since a cost-effective strategy can be designed. The choice of bid analysis is usually made based on risk and reward considerations. In this work, weighted accuracy, precision, F1-score, Jaccard similarity, and profit maximization are calculated and presented for attaining classification effectiveness during bid analysis. These evaluation metrics are apt for measuring and evaluating the classification model’s effectiveness for predictive bid analysis. Profit maximization measures profit or return on investment and can be achieved by leveraging the prediction. The classification model’s predictions are utilized to determine the decision-making process for bid analysis in the problem domain. Choose prediction is denoted as the probability of acceptance and the probability of rejection, which is considered the best reward to pursue.

If the choice prediction for a given classification model is more than 0.5, then the most beneficial decision for the company is to choose the bid. If the choice prediction for a given classification model is less than 0.5, then the decision of the model is influential in rejecting the bid for a specified project scenario in the construction supply chain. Improper selections of bids can be addressed by continuing the exploration of evaluation metrics during model traversal. The construction supply chain's unique nature can take advantage of enhanced execution and the application of deep learning models to reveal hidden insights on the predictive capabilities of the analytical approaches when predicting favorable bid outcomes from a cost-effective perspective. Such a predictive decision can recommend the choice prediction for accepting or rejecting the bids, which brings about cost-effective success.

Equ 2: Cost-Benefit Analysis for Procurement Strategy

$$C_{savings} = \sum_{i=1}^{m} \Delta C_i - \sum_{i=1}^{m} C_i$$

Where:

- ΔC_i is the cost reduction from bid i (compared to the baseline).
- C_i is the original cost of bid i.

4. Case Studies

4.1 Introduction This case study aims to simulate the analysis of the situation in the market for several conditions: theoretical economic situation in the branch, technological possibilities of the market, and expert judgments on the market. The mathematical methods, in this case, are used only for the formalization of expert opinions, which help to improve decision-making quality. However, real data is not used in the analysis.

4.2 Case Study 1: Simulation of Warehouse Business Plan The first case consists of a study with a real company that has little information and aims to show a practical use of the tool. In this supply chain, the data structure steps were not applied because there was not enough time to do the proper data cleaning to be used in the tool. The practical relevance of this case is to offer a predictive analysis tool for final inventory to be used in the simulations of warehouse business plans applying real data and following the steps. In this particular case, the tool was used to compare two unmodern retail store strategies. This analysis aimed to determine whether it made a difference for the simulation of a startup warehouse company.

4.3 A Personal Experience with the Tool Case 2 describes a personal experience that sought to use the tool to help with business intelligence analysis to conduct a market study. The data used was the prediction of the final inventory calculated from a forecast model. The purpose of this work was to present how to use the tool in a real context and create a practical application that illustrated the tool in a physically accurate way.

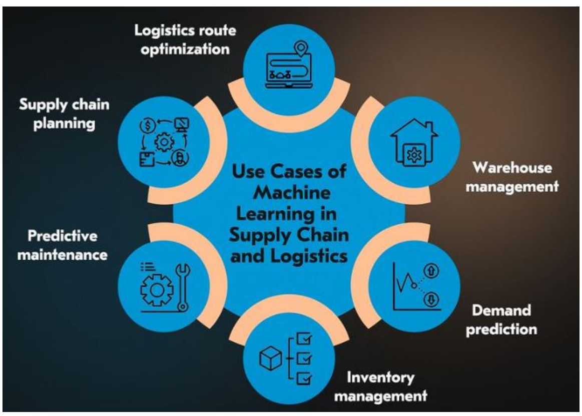

Fig 4: Use Cases of Machine Learning in Supply Chain

4.4. Real-world Applications of Predictive Bid Analysis in Supply Chain Management

In this section, we further discuss the real-world applications of predictive bid analysis in the procurement subdomain of supply chain management. The focus is on strategic sourcing considerations and the computational methods required to support them along with their strategic impact. We draw from theoretical and practitioner views to justify the list developed and detail the requirements and considerations needed for successful implementation. We highlight the importance and relevance of using machine learning approaches such as artificial intelligence for businesses to explore changes in their sourcing needs as a result of this technological revolution that we are about to experience. Strategic sourcing using predictive bid analysis has several self-explanatory, value-added applications in business, which provide complementary support to the procurement value addition of managing costs and delivering exceptional quality. At the highest level, strategic sourcing in procurement is considered a decision-making process, and predictive analysis can be a tool to improve it. We provide some theory-based definitions and some real-time applications. The current most sophisticated technique that firms use is benchmarking with best-in-class supplier capabilities, but the hallmark of the digital revolution currently underway is the extent to which it provides data in higher quality for every relevant object considered and analyzed. These include organizations, people, competencies, knowledge, intellectual capital, product descriptions, and performance parameters.

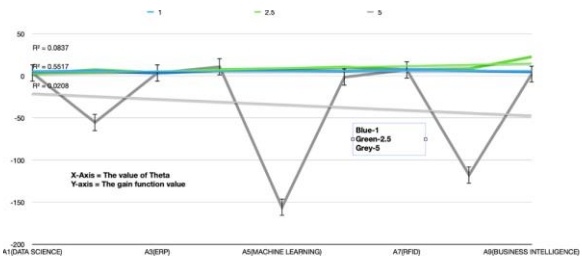

Fig 5: Impact of big data analytics on supply chain performance

5. Conclusion and Future Directions

The research work discussed in this paper explores the usage of AI (artificial intelligence) and ML (machine learning) techniques such as classification, regression, and decision trees for predictive bid analysis in supply chain management. The research forms a sound foundation for strategic decision-making or negotiation preparation on the offered bid quotes from the suppliers. Selecting the right classification algorithm, relying on the power and features of offered algorithms and techniques, and using them as a technique makes supply chain decision-makers' lives easier and less complicated. Larger industrial and real-world data set analysis using large-scale public platforms are possibilities for future research. Even though research work can influence some validity issues like model selection, tie-breaking metrics, preliminary analysis of complex modeling, and multicollinearity, empirical analysis will make quantitative research statistically valid and rigorous, adding value to the model outcomes. Future research can pursue explorations with deep learning algorithms and techniques for obtaining the real gradient estimates. Hybrid models can be a good investment in the industry, as they can detect more complex issues. These are complex and focused on varied types of data and usage for timely support, and traditional AI, ML, and DE can be unique opportunities for future studies in hardware supplier selection. Additionally, supply chain research can benefit from other optimization tools such as AI, machine learning, DE, and other computational optimization techniques, which can further enhance performance.

Equ 3: Bid Optimization Problem

$$\sum_{i=1}^{m} x_i = 1 \quad (Constraint\ on\ selection)$$

Where:

- C_i is the cost of bid i.
- x_i is a binary variable indicating whether bid i is selected (1 if selected, 0 if not).
- m is the total number of bids being evaluated.

5.1. Summary of Findings

Our main findings are threefold. First, we introduce a set of single bid optimization heuristics applicable to any type of bid data. The best performing heuristic is a genetic algorithm using two mating and one mutation operation. This approach improves costs by 800,000 or 28% on average compared to no optimization. Second, we show that AI and ML enable the development of more advanced electronic marketplaces for bilateral negotiations. Heuristic approaches, like the ones presented in this work, can be directly integrated and further improve upon the basic bid management. Simple or nodal auctions might attract more buyers if the number of items or categories is high. If the auction is losing against a different heuristic that we present, buyers are required to have either value estimations or valuations of the specific auction model. These predictions might be provided by an advanced e-commerce company serving as an independent escrow node.

The heuristics specifically designed for these kinds of prediction result in the same savings as the genetic optimization and thus combine auctions with a more advanced optimization strategy. Optimization heuristics can be viewed as an approach to firm-specific price management. Both high savings and a good number of bidding rounds can be achieved. Third, we identified characteristics that influence the extent to which good auction performance is achieved. Tradability is often enough. The value gain of the auction is largely supported by the underlying procurement demands and supply side characteristics. For example, existing internal auctions always deliver extraordinarily good results due to their hybrid combination of solicited prices and over-award factors. Free text fields and the diversity of buying companies are also relevant. Prices can mostly be influenced for homogeneous material groups.

5.2. Implications for Supply Chain Management

Supply chain management leverages various AI and problem-solving technologies, such as optimization methods and simulations, to solve complex tasks. Supply chain management problems with large numbers of decision variables, complex and dynamic structures, traditionally use standard survey tools like linear programming, resource-constrained methodologies, and other operations research procedures. These approaches require a priori specification of the structure of underlying relationships to solve the complex supply chain problems effectively. They fail, however, when the nature or structure of problems cannot be simplified or evaluated explicitly. Recent research in AI, particularly machine learning technologies, has begun to show promise in overcoming such limitations. These new approaches use training data to build a relationship that is a statistical model of the complex problem as opposed to explicit relationships.

More complex optimization problems, like time-dependent vehicle routing, can now be approximated within a few seconds using AI-generated upper bounds. AI and machine learning tools can be effectively used to solve supplier selection problems and inventory replenishment with stochastic demand. An important feature of these technologies is that significant data is available across many operational contexts, which can be used to train and validate algorithms via data mining and careful experimentation. Such algorithms will be more robust and useful under real-world conditions and able to capture complex relationships, especially if problem formulations contain uncertainty and instabilities.

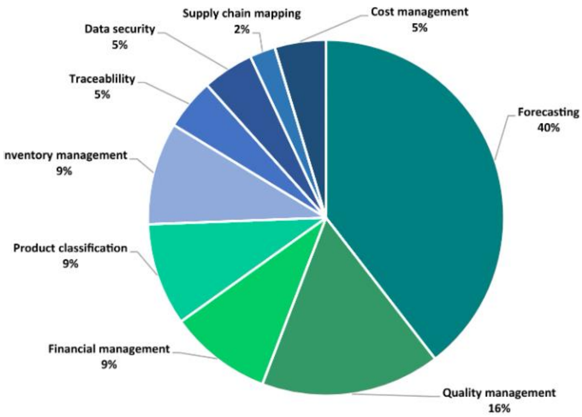

Fig 6: Applications of deep learning into supply chain management: a systematic literature review and a framework for future research

5.3. Future Trends

Predictive bid analytics is an integral and critical tool in the decision-making process for procurement functions. It will continue to evolve and expand in terms of capabilities and scope as AI and ML technologies grow more sophisticated. While the future of predictive procurement analytics is bright, there are a few global trends that are likely to influence how predictive procurement analytics will shape businesses tomorrow. These include data quality and skills; AI and ML; advanced analytics techniques; transparency, bias, explainability, and ethics; algorithm marketplaces and business applications; and new user experiences and interfaces.

First, the quality of data and the skills required to analyze this data are critical. To cope with the increasing volume, velocity, and variety of data, companies need better tools and skills to participate. AI and ML, combined with point-and-click tools, automation, and user interfaces, will help data analysts leverage predictive techniques, supplementing their expertise with capabilities such as automated machine learning. Furthermore, data consumers without an analytical background need interfaces that can present them with the insights they need and guide them to better-quality decision-making. Industries will also experience increased standardization and higher quality levels around advanced analytics, as AI and ML become embedded in a growing array of applications.

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