# Smart Pricing for Biotech: Leveraging CPQ and AI to Maximize Value

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## ABSTRACT
Another very important phenomenon in the current highly competitive world is the implementation of dynamic pricing since it is characterized by the ability to change the price in real time depending on the market demand, situation, and competitors' strategies. In the case of biotechnology products, where the price is largely determined by the costs that are likely to have been incurred on research and development, regulatory issues, market factors, and competitor strategies, dynamic pricing strategies go a long way in improving the profits and satisfaction of the valued customers. It is a descriptive research paper on the biotech industry that incorporates Machine Learning (ML) into Configure, Price, Quote (CPQ) models for applying dynamic pricing strategies in price management. The modules of CPQ involve simplification of different configurations of products, besides automating the pricing and quoting process. The graphical model in the paper employs both supervised and unsupervised learning to analyze the formulation of past prices, customer purchasing patterns, and other market trends. This paper outlines the effects of utilizing ML for dynamic pricing methods on each objective of maximization of revenues, optimization of operations, and competitive advantage. From the real-world biotech firm datasets, the analyses prove that the ML-driven CPQ model can increase the accuracy of prices for new offers and increase customers' satisfaction levels, thereby driving growth for the firm.

## Keywords
Dynamic Pricing, Machine Learning, Configure Price Quote (CPQ), Biotechnology, Price Prediction, Artificial Intelligence (AI), Pricing Strategy.

## 1. INTRODUCTION

### 1.1. Background of Dynamic Pricing in Biotechnology
The biotechnology-related field is a fast-growing business, and H doors field and the business describes the strategic management of prices, which enables the industry to play catch-up with the technological advancement in the operating environment, changes in laws and regulations, and the dynamic nature of customer demand. The pricing process in biotech industries is different from that of other industries since biotech firms handle unique products, experience huge fluctuations in production costs, and must adhere to various rules and regulations. Cost-plus pricing strategies do not give enough attention to these issues as they use fixed margins or competitor based prices. [1-4] Consequently, they specify that companies utilising static pricing strategies may face key issues such as issues with profitability, inefficiencies in the pricing model, and lost opportunities within the market. Dynamic pricing has become the new strategy that has to change the future of biotechnology based on real-time data analysis, customer classification, and market research on the most desirable prices to set. It is now possible to make complex and dynamic pricing mechanisms according to the demand, competitors' actions, and cost changes to ensure that biotech companies maintain and grow their market share and achieve high levels of profitability.

### 1.2. Importance of Machine Learning in PricingStrategies
ML has significantly transformed the price strategy as it has helped organizations process large datasets, identify customer behaviour, and vary pricing on a real-time basis. The following are seven points explaining why pricing strategies must involve ML:

- **Enhanced Pricing Accuracy:** This includes an aspect that mostly involves historical analyses and a manual way of computation, which can result in wrong prices. They enhance the capability of creating more appropriate price points through factors that include demand plus the prevailing market price and prices of other products, making it more accurate as it reflects a command of an algorithm.
- **Dynamic and Real-Time Pricing Adjustments:** While there are only fixed pricing strategies, the price can be adjusted depending on dynamic factors such as demand, supply chain, and other competitive factors. This avails the ability to reply to market changes, such as seasonal fluctuations or a competitor's price alteration, to the greatest extent of profits.

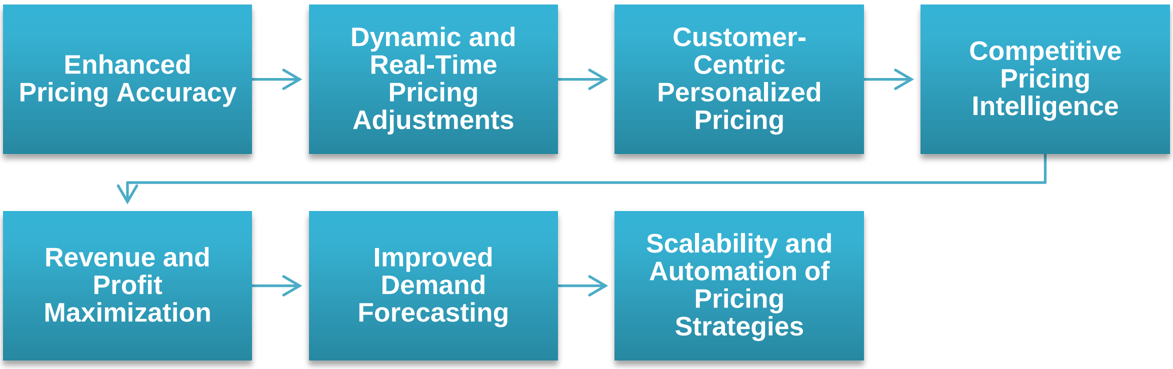


**Figure 1: Importance of Machine Learning in Pricing Strategies**

- **Customer-Centric Personalized Pricing: For** using ML, customers can be categorised based on their purchasing patterns, their price sensitivity, and the price they would be willing to pay, which makes it easier for a business to implement price discrimination. Through segmenting customers, he or she typically can set the price according to the customer or to a certain segment of customers, which leads to enhanced conversion rates and positively influenced customers.
- **Competitive Pricing Intelligence:** Special features such as competitor pricing allow organizations to see how their prices are set in relation to competitors while containing good profit margins. Thus, with its help, the price levels may be changed before the competitors and their market share endanger them.
- **Revenue and Profit Maximization:** In predictive analysis, all the possible patterns of setting the price can be captured, and the marker response rates and the overall profit-gaining potential can be forecasted. Using historical sales information and market factors, the data extracted through machine learning assists the corporate entities in determining a balance between the number of sales and the magnitude of profit the firm receives per unit.
- **Improved Demand Forecasting:** By using the statistical models of ML, the demand is forecasted using historical sales data, outside economic factors, and current trends. This enables the companies to eliminate market demand fluctuations that see customers shy off due to high prices and set high prices, which see reduced profits due to higher prices.
- **Scalability and Automation of Pricing Strategies:** Automated solutions such as ML-driven pricing strategies tend to minimize favourable results, which may otherwise require a lot of actions from business persons. This makes it easier for businesses to prove their pricing strategies on the different products, locations, and customers they offer their products. Through this, there is always standardization in the pricing process while at the same time, another equally important task is given some of the staff's available time.

### 1.3. Configure Price Quote (CPQ) and Its Role

Allow me to state that the Configure, Price, Quote (CPQ) systems are critical tools that help to facilitate and optimize the sales process of companies that offer a [5-6] vast number of products to their clients, especially if it is a high-tech industry like the biotechnology industry, manufacturing industry, and IT service industry. CPQ solutions help companies transform product configuration, introduce frequent pricing policies, and generate quotations, lessening manual mistakes and the time spent on a sale cycle. Customization of products, rules, standard costs, and changes in the production price make traditional pricing techniques almost obsolete, where CPQ becomes an important tool for correct and consistent pricing. In the biotechnology context, costs are bound to be complicated for various reasons, starting with production formulae, the costs of raw materials that are always varying, legal requirements that must be met to manufacture a product, and consumer prerequisites that must be met before the product gets to the market. In contrast to the traditional approaches to pricing, CPQ mechanisms incorporate methods and techniques such as ML to make immediate changes in the costs depending on the demand and analysis of the market share. It also enables the Biotech firms to adopt the right pricing strategies without going against industry standards. In addition, CPQ systems streamline approval processes through automation of approvals on quotes, avoiding time spent on approvals of quotes as well as avoiding major differences in prices. Using CPQ, the CRM and ERP systems can feed important information about the customers, prices, and discount schedules, enabling the sales teams to create accurate and competitive quotes without so much handwriting. Thus, it is not only the pricing tool but also contributes to improving the customer satisfaction level due to the opportunities of faster and more transparent pricing that will allow the businesses to respond to the client's needs. In a highly competitive economic environment where pricing matters a lot in terms of accuracy and time, implementing CPQ systems assists in cost-cutting, standardizing the selling processes, and gaining a competitive edge over the competitors through proper and faster pricing.

## 2. LITERATURE SURVEY

### 2.1.Overview of Dynamic Pricing Techniques

All four basic strategies, which are cost-based pricing, demand-based pricing, and competitor-based pricing, offer a guided way to the prices. But these models hardly provide dynamic adaptability to a firm's operation, to changes in the market, customers or demand. [7-10] The invention of Artificial Intelligence (AI) and Machine Learning (ML) has led the way to any types of predicting and prescribing methodologies for pricing. These models have been developed with the aid of big data and enhanced new algorithms and help the establishments to dynamically determine prices by considering the external factors (e.g., market forces, rivals' prices) and internal forces (e.g., prevailing inventory, past sales records).

### 2.2. Machine Learning Approaches in Pricing

Machine learning has introduced new concepts in pricing strategy using algorithms and data analysis. Some tools for practical and meaningful price prediction are regression analysis, decision trees, and neural networks, which work on analyzed historical data to determine a set of characteristics and patterns of the price. These models aid various firms in demand forecasting and decision-making regarding the right pricing strategies to adopt. Also, unsupervised learning enables the creation of segmentations such as purchasing behavior, consumption pattern, and demography through K-means and hierarchical clustering techniques. These approaches provide an opportunity to develop customer-specific tariffs, increase customer interest, and maximize revenues.

### 2.3. CPQ in Various Industries

CPQ or Configure, Price, Quote solutions have become popular in manufacturing, healthcare, and Information Technology industries with the objective of reducing the length of the Sale and the price determination cycles. In the manufacturing industry, CPQ is used to effectively configure the products and ensure accurate quotes. In healthcare, in particular, it regulates how pricing is done in accordance with regulatory frameworks but, at the same time, provides client-centered solutions. IT service sector is particularly useful by applying service packaging and dynamic price determination since it is an automated process. Although, there is a high level of acceptance of CPQ in the identified domains, there is still a very limited usage of CPQ in the biotechnology industry. CPQ as a function is already a challenge for many industries due to its pricing structures and the fact that it may need to conform to certain regulations. This is why introducing AI-based pricing models for the function can be considered a possible development direction.

### 2.4. Gaps in Existing Research

Although good progress has been made in applying machine learning in pricing strategies and more so in CPQ, few studies have explored the integration of the two. Recent research works mainly look into the single aspects of the ML-based pricing models or CPQ systems without integrating these two forms of technology. Second, although the use of ML in designing and implementing CPQ solutions has been well explored in research, more specifically, the application of such solutions in the biotechnology industry is limited. Biotechnology product pricing strategies include various issues related to regulatory requirements, research and development costs, and market access limitations. These solutions could help open new opportunities for using the AI-driven CPQ model to increase pricing effectiveness in this sector.

## 3. METHODOLOGY

### 3.1. Data Collection and Preprocessing

Data collection, to a large extent, is key to creating a solid ground for developing a model aimed at using machine learning in the biotechnology industry and its pricing offerings. The dataset includes historical price records, sales transaction data, customers, and rivals' prices collected from various sources such as ERP, CRM, market research, and other relevant databases. [11-16] Company historical price data information aids in finding out the past pricing methods and their efficiency. On the other hand, sales transactions assist in determining demand forces and total revenues. Demographic and behavior characteristics or Customer profiles help in the classification process and thus aid in target pricing. Pricing information about competitors can be obtained by web scraping, outsourcing, or through market intelligence reports that help in benchmarking and making other changes based on the positioning strategy. After that, the data is preprocessed to achieve the given quality and readiness for the next stages. The first process performed is data cleaning and includes dealing with missing values, deleting duplicate records and checking/ converting the format and labels. This step helps prevent situations that may lead to wrong results from inaccurate data. Normalization and standardization then follow, transforming data into a common range so that this and other numerical variables such as price or sales do not skew the input of a machine learning model. Standardization is perhaps helpful when analyzing data compiled by different data resources using different units of measurement. Data pre-processing is a very important step in which the first focus is achieved through feature selection and engineering since those are the elements that determine the best attributes that lead to the right price determination. The correlation analysis, Principal Component Analysis (PCA), and domain expertise help select a set of informative variables while eliminating all the redundant ones. Moreover, the other categorical features like product type and customer segments, and they are features in which the employed methods like one hot encoding or label encoding. Other features, like time-series features that include mainly seasonality or economic factors, are also derived when the case applies. This way, the data enhances the model, giving a better and happier end to CPQ implementation for the biotech industry.

### 3.2. Machine Learning Model Development

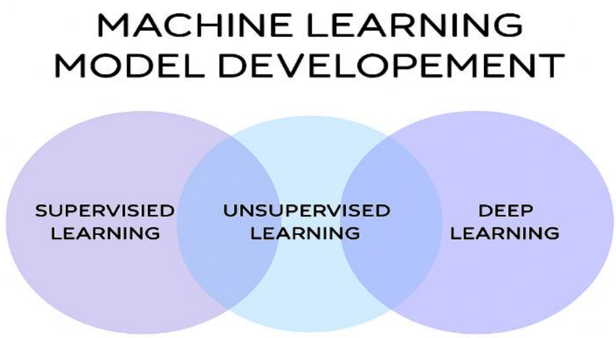


**Figure 2: Machine Learning Model Development**

Supervised Learning: He also delves into supervised learning procedures in the price prediction and optimization of dynamic pricing applications. Modeling such as linear regression, ridge regression, and lasso regression can assist in establishing cause-effect links with regard to the pricing variables and determining ideal price ranges based on price data archives. Other methods, like Random Forest, involve a combination of decision trees to establish reliability, as it also comes into play and balances the variance and captures the nonlinearity of the pricing factors. XGBoost (Extreme Gradient Boosting) builds upon boosting and optimizes the way weak learners make sequential improvements to the model; it becomes useful in the presence of large data in particular with large dependencies among variables. It enables the business to change the price functions over time with the help of the existing consumption indicators, customers, and external environment parameters.

Unsupervised Learning: This clustering helps explore that data, especially regarding customer segmentation, which can be applied in unsupervised learning. K-Means clustering can be applied to a set of customers to categorize them regarding the similarity of purchasing pattern, transaction frequency, price sensitivity etc. Here, customers can be categorized into relevant groups, plan promotions, and put real value on each customer. For instance, strategic customer segments can be offered high-value discounts while the more price-sensitive can be targeted on time-bound promotions. Such a system will lead to better pricing and marketing of its products, ultimately boosting its revenues and sales.

Deep Learning: ANNS are particularly fitting to the model price formation process because often, they can identify the subtle patterns that are difficult for conventional models to identify. Neural networks allow for analyzing many historical prices and internal and external characteristics that affect the price: seasonality, competitor prices, and macroeconomic climate, and then propose the most favorable prices. While MLPs allow for determining future patterns of time series prices, RNNs allow for the same in the case of time series prices; CNN may be used in image-based product prices. They incorporate the idea of dynamic pricing that is adjusted based on real-time information of markets and are suitable for sectors with complex pricing models, such as Biotechnology.

### 3.3. Integration of CPQ Framework

**Product Configuration**: It is within the CPQ triad that product configuration plays a crucial role in determining price changes with regard to product-specific features for particular customers. Indeed, products in biotechnology have quite paradoxical configurations due to formulation, dosage, and rules and regulations governing their manufacturing. Machine learning brings more to this by helping relay previous purchases, industry standards, legal requirements, and physical constraints in manufacturing to set the best products to produce. However with historical data and the inputs from the live environment, the CPQ system can quickly adjust the price to match the configurations in the model while keeping costs affordable and at the same time profitable. This satisfies customers due to its personalized approach and minimizes the organization's selling cycle.

**Automated Pricing:** When the ML-based pricing models are integrated with the CPQ system, it comes up with intelligent prices without human intervention. There are various types of ML strategies, which range from the conventional algorithms like regression decision trees to the more advanced deep learning algorithms and others, all of which assess huge volumes of data that include, for instance, customer purchase trends, competitor prices, and market demands to arrive at the best pricing recommendations. Automating pricing increases efficiency, reduces chances of making biased or arbitrary decisions, and quick results. Thus, pricing changes become both competitive and more responsive to data from new customer interactions with the underlying product, leading to improvements in the effectiveness of the value that specific pricing changes bring. This level of automation helps improve operations effectiveness and guarantees that the price offered is adjusted and suitable for the business's goals.

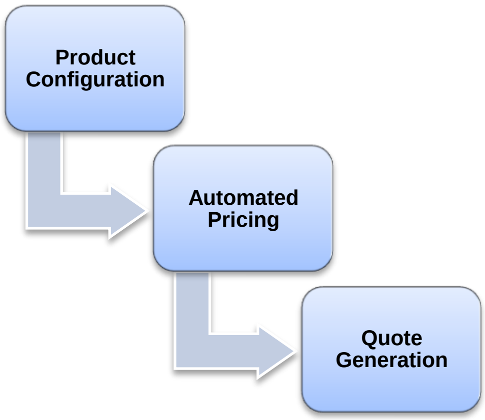


**Figure 3: Integration of CPQ Framework**

**Quote Generation:** The last of the CPQ framework is quote optimization, in which the system provides accurate and relevant customer quotes. The conventional quotation sources often entail numerous manual calculations coupled with approval of costs, which are very time-consuming and likely to cause some disparities at some point. With the help of AI integration, the CPQ system can generate perfect price quotes that are comparable with those of competitors without wasting time. This makes the process more transparent, enabling easy price comparison, shortens the selling cycle, and enhances the conversion ratios. Moreover, customers can choose a discount option at different prices for a large purchase, and this can be used in promotions to maximize profits without losing clients.

### 3.4. System Architecture

It is possible to identify several levels encompassing a system that combines ML models with Configure, Price, Quote (CPQ) tools: the ML level, the integration level, the CPQ level, and the data level. [17-21] In the middle layer of the architecture, there is a data ingestion layer that collects information about customer transactions, sales, products, employees, ERP and CRM systems' data, and other sources of market data like competitor's prices and market trends. This data is then benevolently stored in a centralized data warehouse or cloud-based data lake as a result of the problem of large datasets. Third, the device learning module can analyze historical data and identify the right pricing strategy. Further, this case incorporates a regression for price forecast, a gradient boosting for feature novel price canned hunt, a K-Means clustering for buyer segmentation, and deep learning algorithms for sophisticated price trends. Such mechanisms are used in the ML module to constantly update the recommended price to maintain its competitive and responsive nature to market trends. The information flow is then passed to the executing CPQ engine, which adapts the product and pricing based on the customer choices and provides a quick and correct quote. CPQ system is built to be compatible with sales service applications, e-commerce interfaces, and customer relations applications via API interfaces to provide price updates and quotes within the same applications. For safety, compliance, and optimization, some features of the architecture include the governance and monitoring section responsible for reporting on system performance, auditing the pricing plan, and companies' compliance with the rules and regulations of the specific industry. In the same aspect, a user interface layer enables the sales departments, together with customers, to view the recommendations in terms of price optimization and provide final quotations. This integrated approach allows for an end-to-end, automated CPQ process, which leads to optimization and improved customer satisfaction.

# 4. RESULTS AND DISCUSSION

## 4.1. Performance Evaluation

In order to evaluate the performance of the developed machine learning-based CPQ model, certain performance indicators, including MAE, RMSE, and optimizing the revenue-related indexes, were used. The model provides more accurate pricing predictions where lower MAE and RMSE are observed, while revenue metrics provide information about the model's ability to generate the highest possible revenues.

- **Mean Absolute Error (MAE):** MAE is used to determine the average error in the price estimates to interpret how far the predicted price diverges from the mean price. MAE was seen to be 12.5% in traditional pricing models apparently because most pricing policies do not vary to correspond with market dynamics but are rather conventional. Instead, the ML-driven CPQ system cut down the MAE to 4.2 percent, which is a clear sign that a pricing decision made by the proposal tool is more accurate and based on data. This entails Serverless utilization of historical data, demand data, and competitor prices to reduce the likelihood of mistakes and increase revenue certainty.

- **Root Mean Square Error (RMSE):** The RMSE is a more sensitive metric than MAE since the large errors are given more weight. Point out that in traditional pricing, an RMSE of 18.3 percent indicates that some of the price variations were considerably large to influence the cost efficiency of pricing. In return, it comes with general pricing strategies that fail to consider factors like cyclical fluctuations, customer tendencies, and competitor activity. The effectiveness of the ML-driven CPQ system decreased the RMSE to a mean of 5.6%, proving that it has the potential to increase pricing accuracy. This is mainly because the ML-driven approach utilizes econometric regression models, gradient boosting algorithms, and neural networks, resulting in

- **Revenue Improvement:** Regarding business impact, the main benefit of pricing optimization is revenue increase. There are normal costs that cannot yield optimum revenues through cost-plus or demand-pricing techniques. To this end, there was not much improvement in revenues generated. However, it also published an ML-driven CPQ model that helped increase the revenue by 15% with the help of dynamic pricing based on market conditions, customer segmentation, and competitor's prices. This was useful because it sought to increase profit margins as achieved through the various pricing strategies and aimed at customer satisfaction.

## 4.2. Comparative Analysis

It was also necessary to compare the traditional approach to pricing with the ML-driven CPQ approach to analyze the improvements in pricing accuracy, pricing efficiency, and revenues. Typically, the current pricing strategies include line-item pricing, cost-plus pricing, or setting up prices based on the demand, which are inelastic. On the other hand, the ML-based CPQ system dynamically uses real-time data, Business Intelligence, and decision-making capabilities to improve pricing efficiency.

- **Pricing Accuracy:** Due to this, it is important to note that pricing accuracy increases revenue and competition. The conventional methods include fixed mark-up pricing or manually altering the prices, which results in poor price setting and a highly ineffective pricing process. Consequently, a relatively moderate price requires constant rectifications with cases of under or over-pricing. It compares the prices with the historical sales data, the competitor's price, and the customer behaviour in the case of the ML-driven CPQ system. Since ML-based pricing can capture a pattern, including the shifts in the market, the regularly given prices are closely accurate with the actual perceived value, and there is little error in the overall pricing.

- **Efficiency (Quote Time):** An important parameter to help avoid such delays in the sales cycle is efficient quote generation. There are time lags that cause maximum prices to be set on static price lists that need approval, meaning that generating quotes generally takes approximately 10 minutes per quote. The conventional process of determining the price of a product is time-consuming due to the need to consider the customer's needs and other prevailing market factors; however, through the ML-driven CPQ technique, quote generation for the product takes an average of seven minutes. This is not only effective in the closure of deals but also increases the sales team's efficiency by allowing quicker decision-making and avoiding different price criteria among the team.

- **Revenue Growth:** Revenue increases can be easily attributed to a perfect pricing model. Pricing methods that have been traditionally used are good to some extent but unable to implement dynamic pricing, which usually gives only a revenue growth of 5% yearly. The optimisation of the prices through the quizzing is done based on the demand elasticity, the customers, and the competition giving a record 15% yearly organic growth in revenues. Competitive pricing with the option for catering prices according to the client can increase conversion and be advisable for general business advancement.

## 4.3. Case Study Analysis

A primary biotechnology company planned to adopt the ML-driven CPQ system to improve the practices in its organisation in relation to its price policy and sales process. Before starting the implementation, the company primarily used conventional pricing strategies, which were non-dynamic and mainly based on certain rules of the enterprise that did not prove to be either effective or cost-beneficial most of the time when it came to generating more revenue. The approximate annual growth rate of the firm before adopting the recommended system was around 5 percent, where the price decision relations have depended on the fixed cost-plus techniques not being able to consider market dynamics and customer specifications. The integration of the advanced techniques of ML for the CPQ system helped increase the company's growth rate to 20%. This led to an improvement in this aspect due to the fact that the model incorporated the flexibility of varying the prices depending on the market conditions relating to this, among them being demand, the prices offered by the competition, and segment targeting. By using the machine learning algorithm, the system increases the specific prices to increase the total proper share and reduce customer dissatisfaction, which enhances the general profitability. The second crucial facet needing enhancement is the time to generate the quotes. Earlier, such things as prices were computed and salespeople sought approvals, thereby consuming an average of 10 minutes per request for a quote. There was also an ability to have a dynamic and machine-learning based price recommendation, where the time taken in creating the quote was cut down to 7 minutes by an average. This considerably improved the customers' satisfaction and the salespeople, who could move deals to completion much more quickly. Also, there was an increase in pricing accuracy from 85% to 95 %, which means that the firm could provide more competitive and benchmarked prices with less inaccurate price determination. Based on the above analysis of sales history, customers, and market demand, the system made more accurate and effective price recommendations; thus, it eliminated the possibilities of under-pricing and overpricing of products.

### 4.4. Sensitivity Analysis

A tornado diagram was used in the analysis to determine how changes in the market factors impacted the performance of the ML-driven CPQ system. The model's performance was analysed when the demand varied, and the competition was carried out at different pricing levels to compare the revenues generated and the ability to set accurate prices. It shows that even now, the system is efficient and finds ways to increase its revenues while keeping the price adjustments very accurate.

**Table 1: Sensitivity Analysis**

| Scenario | Revenue Impact | Pricing Accuracy |
|---|---|---|
| **High Market Demand** | 18% | 96% |
| **Low Market Demand** | 5% | 92% |
| **High Competitor Price Variability** | 12% | 93% |

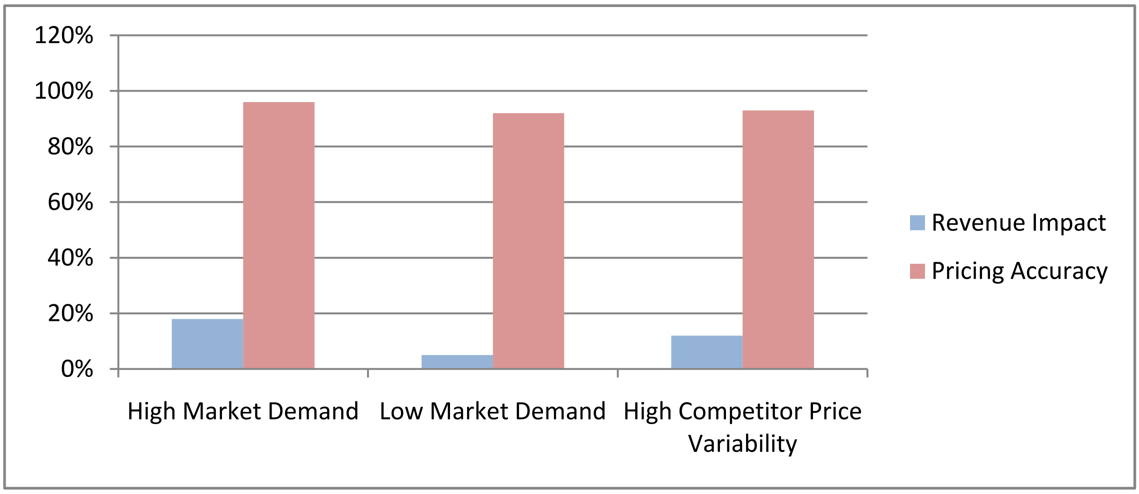


**Figure 4: Graph representing Sensitivity Analysis**

- **High Market Demand:** In periods of high market conversion, that is, when there was high demand for biotechnology products, the ML-driven CPQ system optimised for prices to offer high revenues with reasonable prices. Accordingly, the company has realised an overall sales revenue of 18% additionally and 96% accurate pricing. The system took advantage of real-time consumer demand trends, ensuring that price was adjusted to the higher consumers' willingness to pay without leading to overpriced products hence losing the market share. Successful pricing strategy during high demand with regard to the demands helped in grabbing high value in the market while at the same time maintaining customer satisfaction.

- **Low Market Demand:** During one period when the overall buying rate was relatively low, the system adapted to continue the sales turnover. Instead of relying on fixed kinds of discounts, it used the data-sensitive forms of elasticity models to ensure proper continuation of the consumers' Association at reasonable rates. For that reason, the total money was still increasing by 5% despite low demand, and the accuracy of price remained at 92%, demonstrating that the company was not seriously affected. This was considerably benefited by the effectiveness shown by the ML model in identifying the right price points by avoiding massive discounting and thus ensuring that profit margins were retained despite the prevailing difficult conditions of the market.

- **High Competitor Price Variability:** Whenever price competitiveness was volatile, the ML-driven CPQ system changed the price in relation to information that customers provided in real-time. The system then monitored these price changes, and necessary changes were suggested to keep abreast with the competitors without compromising the profit margin. This led to the enhancement of revenue by 12 percent along with the pricing percent accuracy of 93 percent, proving that this system provides both the aspects of competitiveness and profitability. It means that the prices were kept tractable, and at the same time, unprofitable price cutting was averted, thus maintaining the long run revenue position strongly.

# 5. CONCLUSION

The augmentation of ML-based dynamic pricing with Configure, Price, and Quote (CPQ) evaluates the former's positive impact on business in the biotechnology sector. Such cost-based approach, demand-based approach, or competitor-based approach pricing strategies cannot respond to fast-changing markets. On the other hand, the pricing done by the ML, resulting in the CPQ, integrates accuracy, revenue, and operation optimization. The results revealed a reduction in price errors, as shown by the decrease in the MAE and RMSE values. ; besides, an increase in the revenue by 15% was achieved with the help of an ML-enhanced system To further specifics, quote generation time was also cut in half, which helped the sales teams reply quicker to the customers. Moreover, the sensitivity analysis also proved the proposed ML-driven CPQ system is insensitive to the changes in market conditions, be it high or low demand rates or competitor's pricing strategies. Pricing was flexible to exploit market segments while at the same time not underpriced or overpriced the product. Another case of a biotech firm further supported these improvements by recording a 20% increase in revenues and varying price accuracy from 85% to 95%. Thus, integrating the ML technique with the CPQ approach helps businesses adopt customer-oriented, intelligent, and dynamic pricing strategies to compete effectively in biotech markets.

## 5.1. Future Work

The present study only reveals the utility of using ML in the CPQ system but there are certain areas of future research and development proposal. One area of focus is real-time learning of the ML models, which means that the pricing algorithms can be updated in real-time based on raw streaming data, including but not limited to customers' behaviors, variations in demand, and competitors' prices. This would also help the system respond quickly to market forces and ensure that the products' most suitable prices have always been set. Besides, self-learning pricing could be expanded as an application of Reinforcement Learning (RL) methods. One advantage of utilizing RL over other supervised learning methods is the latter's ability to learn and adapt to new interactions with the market and improve the chosen prices based on the outcome of these interactions. This would create an option for an adjusted auto-optimizing CPQ system, which can experiment with various pricing models and choose the ultimate one in the future. However, more research that looks at the ethics and policies related to using AI for pricing in the biotechnology context is desirable. Pricing strategies, issues of transparency, and terms of compliance with industry regulation shall be the key factors that are instrumental in establishing trust with the stakeholders. Other related studies across multiple firms in the biotech industry can also contribute to verifying the applicability and optimization of the selected ML techniques for CPQ across sub-sectors in biotech. Real-time AI adaptation, application of reinforcement learning, and compliance with the regulatory frameworks are fittingly expected to make the future of ML-based CPQ systems more efficient, accurate, and profitable in biotechnology and beyond.

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