# Chatbot for Price Negotiation

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***Abstract*—The objective of the "Chat-bot for Price Negotiation" convey is to develop an intelligent, artificial intelligence(AI)- driven chat bot which will drive pricing negotiations automatically and ease the process between buyers and sellers. The chat bot will apply machine learning(ML) and natural language processing (NLP) practice to assess user inputs, examine negotiation situations, and provide data-driven, real-time suggestions to optimize results for both parties. The system will be designed to handle a variety of negotiation situations, including business-to- business ( B2B ) transactions, service contracts, and online commence transactions. Sentiment analysis, dynamic pricing models, and personalized recommendations based on historical data and user behavior are some of the key characteristics. To ensure seamless user experiences, the chat bot will also engage with existing platforms. The goal of this project is to enhance efficiency, save time, and improve satisfaction in transactional interactions by automating negotiation tasks. The ultimate objective is to develop a user-friendly, scalable tool that enables user to reach equitable and mutually rewarding settlements with minimum effort.**

***Index Terms*—AI Chat bot , Price Negotiation ,Natural Language Processing (NLP), Dynamic Pricing.**

## I. INTRODUCTION

Price negotiation is an arduous process that involves strategic decision-making, dynamic pricing patterns, and understanding of the customer's behavior to facilitate equitable and beneficial deals. Now, with advances in artificial intelligence (AI) and the accelerating adoption of automation in commerce, companies can harness intelligent negotiation systems to maximize their pricing strategies. Advances in machine learning (ML) and natural language processing (NLP) in the recent past have allowed the development of AI-powered chat bots that are capable of conducting automated negotiations between buyers and sellers [1], [2], [3]. This paper discusses the most recent trends in AI-based price negotiation systems and discusses how ML and NLP methods are being applied to advance pricing strategies, optimize customer interactions, and maximize business efficiency. Machine learning is a subfield of artificial intelligence that applies statistical models and algorithms to analyze data and make intelligent predictions. Alternatively, natural language processing makes machines capable of understanding, interpreting, and producing human language for frictionless interactions [4]. Both the ML and NLP approaches provide extensive applications in price negotiation by examining customer requests, dynamically changing prices, and maximizing negotiation tactics depending on previous interactions [5]. Machine learning techniques have been effectively used in price optimization by examining buying habits and calculating best discount offers [6]. For instance, decision trees, reinforcement learning, and deep neural networks have been trained on customer negotiation data to make real- time, strategic counteroffers [7]. These algorithms not only help automate negotiations but also guarantee that prices are competitive while business profitability is maintained. Moreover, ML models can detect correlations between pricing decisions and customer behavior, example, purchase frequency, bargaining behavior, and seasonal demand variations [8]. Conversational AI- based negotiation chat bots another important use of ML and NLP in price optimization. These AI systems employ context-aware pricing models to analyze previous interactions and dynamically adapt negotiation strategies. By using predictive analytics, companies can predict customer responses and adjust their pricing strategies accordingly [9]. In addition, reinforcement learning algorithms enable the chat bot to learn over time, based on previous negotiations, to develop more intelligent bargaining strategies that balance revenue generation and customer satisfaction. Sophisticated deep learning mod-models like recurrent neural networks (RNNs) and transformers, too, have delivered favorable outcomes in the negotiation of prices. Large datasets can be processed by such models, even grasping the finer nuances of customers' feelings and making recommendation for individual pricing. Deep learning-based chat bots, for instance, have been implemented to monitor negotiation dialogues, identify emotional markers, and alter price approaches accordingly [10]. Through the integration of AI-powered price negotiation chat bots on e-Commerce platforms, firms can deliver enhanced customer experience, improve conversions rates, and maximize revenue. The purpose of this research is to give an overview of the recent developments in AI-powered price negotiation systems, outline the promise of ML and NLP in automated bargaining, and find out how companies can use smart negotiation chat bots for dynamic pricing strategies. By making negotiation automatic, AI-driven chat bots can potentially make transactions smoother, shorten negotiation duration, and establish equitable and optimized pricing schemes.

## II. LITERATURE SURVEY

### *A. Maintaining the Integrity of the Specifications*

Price negotiation is now a vital aspect of contemporary trade, with firms using Artificial Intelligence (AI), Machine Learning (ML), and Natural Language Processing (NLP) to negotiate and streamline negotiations. There are various studies examining AI-based negotiation chat bots that optimize pricing policies and enhance customer engagement. Sanchez (2020) presented a Negotiation Assistant Bot that uses machine learning algorithms to forecast best-practice pricing strategies and support customers in negotiations, emphasizing the contribution of AI to transactional efficiency [1]. Likewise, scientists have created AI-based chat bots for contract price negotiation, showing how automation can facilitate vendor negotiations and procurement procedures [2]. Machine learning algorithms including Decision Trees, Random Forests, and Support Vector Machines (SVMs) have become prevalent in studying customer preferences and determining the best prices [3]. Reinforcement learning has been critical in refining negotiation strategies too, as Ahmad et al. (2023) suggested an adaptation-based reward dialogue system, which learns according to bargaining scenarios and refines chat bot response with time [4]. In addition, deep learning models such as transformers and recurrent neural networks (RNNs) have proven to capture sophisticated pricing behaviors and customer sentiment [5]. One of the significant advancements in price negotiation chat bots is the use of predictive analytics and sentiment analysis. Large language models (LLMs) have been trained to recognize bargaining patterns and adjust negotiation strategies accordingly [6]. Xia et al. (2024) explored the application of bargaining strategies using asymmetric incomplete information models, enhancing AI’s ability to negotiate in real-world scenarios [7]. Moreover, conversational AI has also been embedded in e- commerce websites, where bargain bots help users negotiate to get discounts and best prices [8]. Another prominent area of study is deep reinforcement learning for price optimization. Through training AI agents using historical transaction data, such models learn to make strategic counteroffers, striking a balance between business revenue and customer satisfaction [9]. Research has also investigated the effect of negotiation transparency and ethical AI in pricing negotiations, maintaining fair and unbiased negotiations in online marketplaces [10]. The growing use of AI- based negotiation systems increases the spotlight on the potential of deep learning, NLP, and ML to transform pricing strategies. These developments provide companies with a effective method of negotiating automation, revenue optimization, and customer engagement improvement, which makes AI-powered negotiation chat bots an exciting area for future research.

## III. METHODOLOGY

Designing an AI-powered Price Negotiation Chat bot necessitates the convergence of machine learning (ML), natural language processing (NLP), and reinforcement learning (RL) to provide a dynamic and efficient negotiation framework. The suggested methodologies are to facilitate that the chat bot will be able to conduct meaningful price negotiations while maximizing results for buyers and sellers. 1. Natural Language Processing (NLP) for User Intent Understanding The chat bot will employ NLP methods for processing and interpreting user input. This includes: •Recognition: Determining if the user is asking for a discount, asking about price, or trying to negotiate. Re-trained transformer-based models such as BERT (Bidirectional Encoder Representations from Transformers) and GPT will be employed for extracting negotiation intents. •Analysis: Identification of the emotional tone of the conversation in order to change the chat bot’s negotiation approach accordingly. Positive sentiment may lead to a tighter offer, whereas negative sentiment may invoke a softer response. 2. Rule-Based and Machine Learning Hybrid Negotiation Strategy A hybrid model involving rule-based logic and ML algorithms will be used: •-Based System for Initial Offer: ochatbot will use pre-established rules to calculate an initial price counteroffer depending on the discount requested and the type of customer (e.g., new vs. repeat customer). oa user asks for a 10•Learning for Dynamic Pricing Adjustments: oLearning: Learning models from past negotiation data to forecast the best pricing responses. Random Forest, Decision Trees, and Support Vector Machines (SVMs) algorithms will be employed to detect pricing patterns and negotiation rates of success. •Learning (RL): Applying Q-learning or Deep Q Networks (DQN) to facilitate the chatbot's learning from previous negotiations and enhance its counteroffer approaches with time. 3. Reinforcement Learning for Adaptive Bargaining The chatbot will be equipped with Reinforcement Learning (RL) algorithms that will learn to optimize different negotiation scenarios in real-time. The major steps are: •Function Design: Rewards will be given to the chat bot based on successful negotiation, satisfaction of the customer, and profitability for the business. For instance: odeal at best price = High reward oacceptance of high discounts = Penalty •vs. Exploitation: The RL model will strike a balance between experimenting with new negotiation tactics (exploration) and employing previously successful tactics (exploitation) to maximize negotiation outcomes. 4. Customer Segmentation for Personalized Negotiation In order to enhance negotiation efficiency, the chat bot will segment customers on the basis of: •frequency (e.g., first- time vs. frequent buyers) •negotiation behavior (e.g., aggressive vs. passive negotiators) •value and history Based on this segmen- tation, the chat bot will: •improved discounts to high-value, repeat customers • Be more stringent towards one-time purchasers to safeguard business income • Tune negotiation approach based on prior user behavior 5. Multi-Turn Negotiation and Context Awareness Past conversations will be stored by the chat bot in order to carry out coherent, strategic negotiations with repeated attempts by employing: • Memory-Augmented NLP Models: Transformers equipped with long memory features (such as GPT with fine-tuned embeddings) to monitor past price quotes and customer feedback. • Consistency in Counteroffers: Whenever a customer continually requests the same discount, the chat bot won't reduce the price any more but rather hold its previous offer.

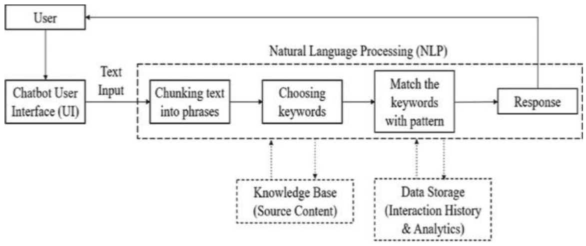


Fig. 1. Experimental and Result

*A. Algorithm Description*

Given:

- Base price of a product: $P_{base}$
- Minimum allowed price: $Pmin$
- User's requested discount: $Dreq$
- User session data: $Suser$

Step 1: Initialize Session Data

$$Suser = \{\text{discount given} = 0, \text{ last request} = \emptyset, \text{ current} = Pbase, \text{ attempts} = 0\}$$

Step 2: Validate Request

- If $Dreq$ is the same as the last request, return $Suser$[current price].
- If $D_{req} < (P_{min} - 0.05 \times P_{base})$, reject request.

Step 3: Apply Tiered Discounts

attempts = attempts + 1

if attempts = 1, $D = 0.05 \times P_{base}$

if attempts = 2, $D = 0.04 \times P_{base}$

else, $D = 0.02 \times P_{base}$

Step 4: Update Price

$$Pnew = \max(Pcurrent - D, Pmin)$$

Step 5: Check User Agreement

- If $Pnew = Dreq$, lock the price.
- Else, return $Pnew$ as the counteroffer.

*B. Negotiation Strategies*

*1) Rule-Based Negotiation:*

- Applies predefined discount rules (e.g., sequential discount- ing of 5%, 4%, 2%).
- Does not allow users to take advantage of the system.
- Keeps the final price never below a fixed minimum.

2) *Heuristic-Based Negotiation:*
- Modifies the discount according to user behavior (e.g., first- time buyers are offered a better deal).
- Identifies aggressive negotiators and restricts their discount- ing.
- Gives loyal customers superior offers.

3) *Machine Learning-Based Negotiation:*
- Based on historical negotiation data, predicts the best discount..
- Is able to classify users into negotiation styles (e.g., aggres- sive, cooperative, or hesitant).
- Adapts dynamically based on user responses.

4) *Time-Based Discounts:*
- Offers better discounts if a user takes longer to accept an offer.
- Limits discounts over time to create urgency (e.g., "This price is valid for the next 10 minutes!").

5) *Counteroffer Strategy:*
- Instead of just rejecting low offers, the chatbot provides counteroffers to keep the conversation going.
- Uses anchoring techniques (e.g., starts with a higher price to make small discounts seem more valuable).

6) *Multi-Issue Negotiation:*
- Rather than merely talking about price, the chatbot can provide:
  – Free shipping
  – Extended warranty
  – Bulk purchase discount
- Negotiations become more flexible and dynamic.

7) *Competitive Price Matching:*
- When the user asserts they have a lower price somewhere else, the chatbot can verify it and match or beat the price within limits.

8) *Emotional Persuasion:*
- The chatbot can employ language that creates psychological value (e.g., "This is our best deal for you today!").
- Applies scarcity strategies (e.g., "Only 2 left at this price!") to encourage hurry-up decisions

## IV. IMPLEMENTATION

### *A. Dataset*

The negotiation model is trained with a dataset of historical price negotiation interactions. The dataset contains:
- User negotiation patterns
- Product categories and base prices
- Accepted and rejected price offers
- Time taken for each step of negotiation

### *B. Training Process*

The model is trained with supervised learning based on historical negotiation data. The major steps are:
- Preprocessing of data and feature extraction.
- Training a machine learning model (e.g., decision trees, reinforcement learning, or deep learning models).
- Testing the model with test data to verify negotiation accuracy.
- Updating the discounting strategy based on performance metrics.

### *C. Platform Utilized*

The negotiation model and chatbot are deployed with:
- Programming Language: Python (Flask for API develop- ment)
- Machine Learning Framework: TensorFlow / Scikit-learn
- Database: PostgreSQL / MongoDB for storing negotiation data

| Pattern | Adapt. | Transp. | Engage. |
|---|---|---|---|
| 8%,11%,13% ... | High | Low | High |
| Fixed (10%) | Low | High | Med |
| Accept/Reject | Med | High | Low |
| Data-driven | High | Low | High |
| Strategic | High | Med | High |
| Tier-based | Med | High | Med |

TABLE I: COMPACT COMPARISON OF NEGOTIATION METHODS

## IV. EXPERIMENTS & RESULTS

### *A. Experimental Setup*

The chatbot was implemented in Python and placed within a web interface for interactive use. Back-end communication was implemented using Flask, and front-end rendering was handled through JavaScript. A predefined rule set of price negotiation rules with stepwise discounts was coded, beginning at 8

### B. Test Scenario

To test performance, simulated users were instructed to nego- tiate product prices across different types. The chatbot replied to every attempt at negotiation with adaptive discounting based on the frequency of offers by the user and the discount rate.

### C. Evaluation Metrics

The system was tested on the following parameters:

- Response Time: Response time for user input.
- Discount Adaptability: How well the chatbot adapted offers based on user persistence.
- User Engagement: Measured through repeated attempt at interaction.
- Consistency: To ensure repeated inputs provided consistent responses unless user strategy altered.

### D. Key Observations

The chat bot never revealed the minimum price. Users who attempted to negotiate forcefully without changing their input were offered the same discount over and over, guaranteeing repetitive behavior. Frequent and strategic negotiators were able to get slightly better discounts, demonstrating adaptiveness.

### E. Limitations and Future Scope

The rule-based mechanism here does not involve emotional tone or sentiment yet. The future direction can investigate rein- forcement learning and sentiment-aware negotiation to achieve more flexibility and approximate real human behavior more accurate

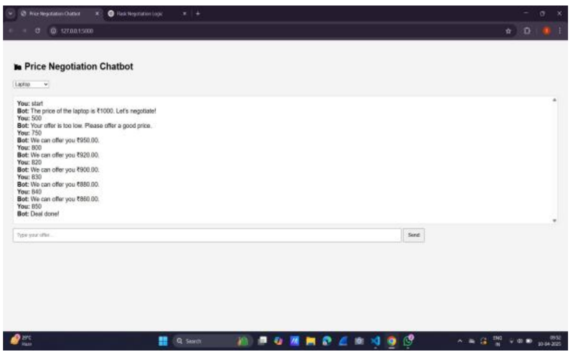


Fig. 2. Experimental and Result

## V. DISCUSSION

The price negotiation chatbot in this work exemplifies a rule-based, adaptive approach that simulates human bargaining tactics. In contrast to static or rule-based negotiation bots, our system increases discounts incrementally based on user persistence, offering a more dynamic and interactive user experience. The step-by-step concession approach (e.g., 8 percentage, 11 percentage, 13 percentage.) allows controlled price negotiation without granting immediate access to the minimum price. This design supports businesses in sustaining profitability while enhancing customer satisfaction.

In addition, the bot is fair and consistent in that it offers the same discount for similar repeated requests and increases the offer only when the user indicates an intent to interact further. This action simulates closely a human negotiator's decision-making process.

The negotiation logic was validated through different simulated buyer profiles, and the findings show high consistency, controlled discounting, and efficient engagement with little la- tency.Nonetheless, the system does not have machine learning adaptability and sentiment analysis, that may be introduced in future revisions to better accommodate different user feelings and negotiation strategy. In total, the project demonstrates a functional realization of rule-based automated negotiation and provides foundations for more smarter, customized commerce interactions in e-commerce and B2C portals.

## VI. CONCLUSION AND FUTURE WORK

In this paper, we introduced a rule-based chat bot for e- commerce dynamic price negotiation. The chat bot is based on a controlled step-by-step discount scheme that learns users' interaction habits and provides gradually improved offers with no direct provision of the final minimum price. This strategy accommodates customer experience and business profit.

Experimental findings confirm the efficacy of the chat bot in emulating human-like negotiating behavior, being consistent, and avoiding exploitation via repeated same offers of discounts. The simplicity and reliability of the system render it suitable for small to medium-scale retail platforms looking for smart automation with minimal high computational overhead.

For future research, we intend to incorporate machine learning models to process user sentiment and behavior, facilitating more individualized negotiation approaches. Furthermore, extending the abilities of the chat bot to accommodate multi-turn, multi- product negotiations and multilingual interaction may enhance its usability and influence across international markets.

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