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NEXT GEN AI FOR SMART E-COMMERCE WEBSITE

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Abstract: This paper proposes an AI-aided e-commerce platform that includes a negotiation-based chatbot that mimics real-world price negotiations. The proposed AI chatbot makes intelligent responses using natural language processing techniques in response to users' price offers. The recommendation engine, using TF-IDF and cosine similarity techniques, maximizes user engagement by recommending products in real time. The secured backend system manages products, users, and order processing, providing users with seamless shopping and purchasing experience. Discounts are provided only to interested users, thus maximizing sales and reducing revenue loss for the business. The proposed system bridges the gap between traditional price negotiations and e-commerce platforms, thus maximizing user retention and business outcomes. Index Terms—AI Chatbot, E-Commerce, Price Negotiation, Natural Language Processing, Recommendation Engine, TF-IDF, Cosine Similarity, Cart Abandonment, Personalized Discounts.

I. INTRODUCTION

E-commerce systems have significantly changed the way customers engage in shopping activities across the world. The systems provide convenient access to millions of products at any time and from anywhere. However, price sensitivity remains a critical component of e-commerce, and a significant percentage of online shoppers abandon their carts if they consider the prices non-negotiable. The prices should be negotiable, especially for customers used to the bargaining culture found in traditional markets. According to the Baymard Institute, nearly half of all online shopping sessions end with cart abandonment, mostly because of price dissatisfaction. The Traditional online system involves flat or seasonal discounts provided to all customers. However this approach has two major disadvantages: first, It causes revenue loss as customers willing to pay the full price, and it still fails to engage users who specifically expect an interactive bargaining experience similar to that found in traditional markets. In order to bridge this important gap, this project makes use of a negotiation-based AI Chatbot that enables customers to inter-actively bargain for the price of products in real time. The Chatbot is developed on top of an open dialogue management architecture that is inspired by Rasa. The Chatbot makes use of NLP-based intent detection and minimum price validation logic to make fair counter-offers to customers. The system ensures that discounts are offered to customers who show genuine interest in price negotiation. This maximizes revenue as well as conversion metrics. Moreover, the system makes use of a recommendation engine to personalize the customer shopping experience. The engine makes use of TF-IDF-based vectorization and cosine similarity scoring to identify and recommend products that are closely related to the customer's current area of interest. The NLP-based preprocessing pipeline is achieved through the NLTK library. The web application layer is developed on top of Flask.

A. Motivation

The underlying motivation behind this work is derived from the behavioral disconnect between offline and online shopping paradigms. In traditional markets, buyers and sellers engage in price negotiations, thus generating a sense of engagement and fairness. However, this does not seem to be the case with online markets, and a certain percentage of price-conscious buyers end up abandoning their shopping carts or feeling unsatisfied with the entire process. The concept of automated price negotiations has been explored under the domain of multi-agent system research, although its adoption in online shopping interfaces is still in its infancy. The system under proposal attempts to provide a sense of intelligent price negotiations via an AI-powered chatbot, thus enhancing the overall shopping experience and reducing the rate of cart abandonment.

B. Problem Statement

Given an e-commerce platform P that host a product catalog C and set minimum pricing constraints M , an AI system A designed so that:

1) Customers are able to make offers using a natural language interface.
2) The AI system makes intelligent counter-offers without violating the minimum price constraints.
3) The AI system provides personalized product recommendations based on the product of interest.
4) The platform provides a secure platform for user authentication and cart management.
5) The platform minimizes Revenue loss by allowing discounts for bargaining customers.

C. Contributions

This paper makes the following specific contributions:

1) We design a negotiation-based AI chatbot that performs dynamic price bargaining using NLP-driven intent classification and minimum price validation.
2) We integrate a TF-IDF and cosine similarity-based recommendation engine that surfaces relevant products in real time based on user browsing context.
3) We implement a secure full-stack backend in Python with MySQL for product management, user authentication, cart lifecycle management, and order processing.
4) We demonstrate that selective, negotiation-triggered discounting achieves superior revenue outcomes compared to universal discount strategies.
5) We provide a comprehensive UML-based system design including class, sequence, state, activity, and data flow diagrams.

The remainder of this paper is organized as follows: Section II reviews related literature; Section III presents the proposed system architecture; Section IV details the methodology; Section V describes implementation details and system requirements; Section VI presents the UML diagrams; Section VII presents expected results and discussion; and Section VIII concludes the paper.

II. LITERATURE SURVEY

Research on AI-driven e-commerce personalization and automated price negotiation spans multiple disciplines including natural language processing, recommender systems, and multiagent systems. This section reviews key prior works relevant to the proposed framework.

A. AutoML for Deep Recommender Systems

A 2022 survey on arXiv reviewed how AutoML techniques optimize deep learning-based recommender systems, enabling scalable and adaptive AI models that automatically tune their architecture and hyperparameters. The work demonstrated that automated model selection can significantly reduce the engineering effort required to deploy high-quality recommendation systems at scale. These insights motivate the adoption of lightweight, deployable recommendation algorithms such as TF-IDF combined with cosine similarity in resource constrained e-commerce environments.

B. AI-Driven Recommendations: A Systematic Review

A 2023 systematic review published in MDPI provided a comprehensive survey of AI-based recommender systems, encompassing machine learning, deep learning, and hybrid models, with integration of emerging technologies such as virtual reality, augmented reality, and blockchain. The review highlighted that collaborative filtering and content-based filtering remain foundational paradigms, and that hybrid approaches combining both consistently outperform single-method systems. The proposed work adopts a content-based filtering strategy using TF-IDF vectorization to enable low-latency, deployment-friendly recommendation without requiring large user interaction histories.

C. Generative AI in Social and E-Commerce Recommendation Systems

A 2024 survey on arXiv focused on real-world use of generative AI in recommendation systems, highlighting frameworks, challenges, and practical industry applications. The survey identified that generative models, including large language models and diffusion-based systems, are increasingly being applied to produce personalized product descriptions, dynamic pricing suggestions, and conversational commerce experiences. The proposed negotiation chatbot draws conceptually from this paradigm by employing NLP models for intent recognition and counter-offer generation within constrained pricing boundaries.

D. Open-Source Dialogue Management

Bocklisch et al. introduced Rasa, an open-source framework for natural language understanding and dialogue management, demonstrating that rule-augmented machine learning pipelines can achieve robust intent classification and entity extraction in constrained domains. The negotiation chatbot proposed in this work adopts a comparable pipeline design, applying tokenization, stop word removal, and stemming via NLTK before passing features to a rule-based intent classifier optimized for the bargaining domain.

E. Foundational Information Retrieval Techniques

The theoretical underpinnings of the recommendation engine rest on classical information retrieval research in automated negotiation. Jones introduced the inverse document frequency (IDF) weighting scheme, establishing the mathematical basis for discriminating informative terms from common ones. Salton and McGill extended this into the TF-IDF vector-space model that now underpins the product similarity computation in the proposed system. The NLP implementation leverages the Python NLTK library, and the complete web stack is assembled using the Flask framework.

F. Identified Research Gaps

Despite the wealth of research on recommender systems and conversational AI, the specific combination of real-time

price negotiation with personalized product recommendation within a unified e-commerce platform remains underexplored. Existing chatbot deployments in e-commerce predominantly address customer service queries such as order tracking and FAQ resolution, without engaging in dynamic pricing interactions. Furthermore, most recommendation research focuses on large-scale collaborative filtering requiring rich user history data, making them unsuitable for cold-start scenarios. The proposed system addresses both gaps through a negotiation-capable chatbot and a content-based recommendation engine operable without historical interaction data, targeting the cart abandonment problem documented in prior research.

III. PROPOSED SYSTEM

A. Existing System Limitations

Most e-commerce platforms provide fixed pricing where users must either accept the listed amount or abandon the purchase. Discounts are generic and universally applied, causing unnecessary profit loss even from non-bargaining customers. Existing chatbots focus only on customer service queries(order tracking, FAQs) and lack any dynamic price negotiation capability. The absence of personalization in pricing strategies frequently results in poor customer satisfaction and decreased conversion rates. There is no interactive mechanism analogous to bargaining in physical retail environments, leading toreduced user engagement and elevated cart abandonment rates.

B. Proposed System Overview

The proposed system introduces an AI-powered negotiation chatbot that allows customers to bargain for better prices in real time. The system enables personalized discounts exclusively for customers who demonstrate active interest in bargaining, thereby preventing excessive revenue loss from customers who would have purchased at full price. NLP and intent classification are used to understand customer price offers and generate intelligent counter-offers. A recommendation engine improves product discovery and enhances the overall shopping experience. The resulting platform provides a more human-like shopping interaction that measurably increases conversions and reduces cart abandonment rates.

C. System Architecture

The system is organized into five primary components:

(i) Frontend Interface: Built with HTML5, CSS3, and JavaScript, the frontend provides an intuitive product browsing

experience, a chat interface for price negotiation, and real-time display of recommended products.

(ii) Negotiation Chatbot Engine: The chatbot processes user price offer inputs through an NLP pipeline that performs document
intent recognition (accept, counter, reject) and validates offers against product-specific minimum price thresholds stored in
the database. The dialogue management design follows the principles of open-source conversational frameworks.
iii) Recommendation Engine: Product descriptions are vectorized using TF-IDF, and cosine similarity scores are computed between the current product and all catalog items. The top-k most similar products are returned as real-time recommendations.
(iv) Backend API: Implemented in Python using the Flask framework, the backend exposes RESTful endpoints for product retrieval, cart management, order placement, user authentication, and chatbot interaction.
(v) Database Layer: MySQL stores product catalog data (including minimum negotiable prices), user credentials, cart state, order history, and negotiation session logs.

IV. METHODOLOGY

A. NLP-Based Intent Recognition

User messages submitted through the chatbot interface are preprocessed through a standard NLP pipeline: tokenization, stop word removal, and stemming using NLTK. Features are extracted and classified into one of three intent categories: offer (user proposes a specific price), accept (user accepts the current offer), or reject (user declines and exits negotiation). A rule-based classifier augmented with keyword pattern matching, inspired by the dialogue management architecture described in, provides reliable intent recognition for the constrained negotiation domain.

B. Negotiation Logic

The negotiation engine implements a threshold-based counter-offer strategy grounded in principles from automated negotiation research in automated negotiation. Let Plisted denote the listed price, Pmin the product's minimum allowable price, and Poffer the customer's submitted offer. The negotiation decision function is defined as:

Accept if $P_{offer} \geq P_{min}$
Response = Counter(P_c) if $P_{offer} < P_{min}$ and rounds $\leq R_{max}$
Reject if rounds $> R_{max}$ (1)

where the counter-offer price Pc is computed as:

$P_c = P_{offer} + \alpha \cdot P_{min} — P_{offer}$ (2)

with $\alpha \in (0, 1)$ controlling the negotiation aggressiveness (step size toward the minimum price), and Rmax the maximum number of negotiation rounds permitted per session.

C. TF-IDF Recommendation Engine

Product descriptions are indexed using TF-IDF vectorization. For a product corpus D = {d , d , . . . , d }, each document
di is transformed into a TF-IDF vector $v_i \in R^m$ .The similarity between the query product dq and each catalog item di is computed
using cosine similarity:

$$\mathrm{sim}(d_q, d_i) = \frac{v_q \cdot v_i}{\|v_q\|\,\|v_i\|} \qquad (3)$$

The top-k products with the highest similarity scores are returned as recommendations, excluding the query product
itself. Compared to collaborative-filtering approaches that require large historical interaction datasets, this content-based method is immediately applicable in cold-start scenarios.

D. Evaluation Metrics

System performance is assessed using the following metrics:

Negotiation Acceptance Rate (NAR): The fraction of negotiation sessions that result in a successful purchase. Revenue Preservation Ratio (RPR): The ratio of revenue collected under selective negotiation discounting versus universal discount strategies.

Recommendation Relevance: Measured using Precision@k and Mean Reciprocal Rank (MRR) on a held-out evaluation set of manually labeled relevant product pairs.

Cart Abandonment Rate:

Compared pre- and post-deployment to quantify the system's impact on purchase completion, using industry benchmarks from the

Baymard Institue.

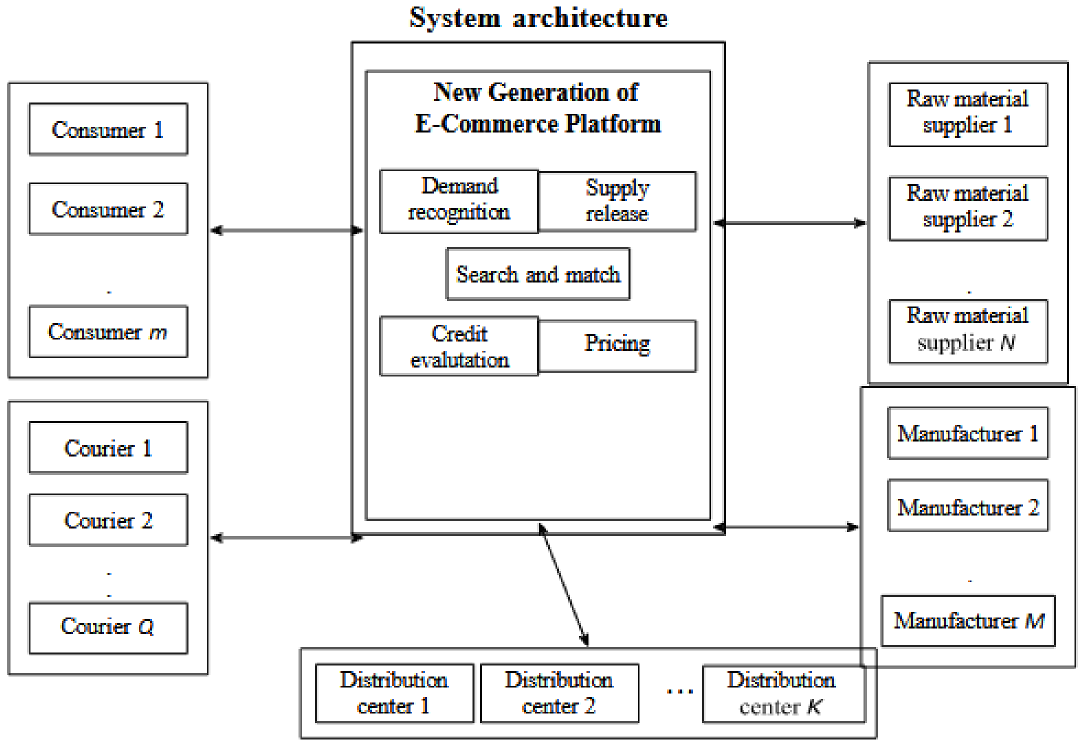

Fig. 1. System Architecture of the Next Generation E-Commerce Platform

V. IMPLEMENTATION DETAILS

A. Technology Stack

The complete technology stack is summarized in . The backend REST API is implemented with Flask, NLP preprocessing with NLTK, and machine learning utilities with scikit-learn and TensorFlow. The TF-IDF vectorizer follows the formulation of Salton and McGill.

TABLE I
SYSTEM TECHNOLOGY STACK

Component	Technology
Frontend	HTML5, CSS3, JavaScript
Backend	Python (Flask)
Database	MySQL
NLP Library	NLTK
ML Libraries	TensorFlow, scikit-learn
Recommendation	TF-IDF + Cosine Similarity
IDE	Visual Studio Code
Version Control	Git

A. Hardware Requirements

TABLE II
HARDWARE SPECIFICATIONS

Component	Specification
Processor	Intel Core i3 or equivalent
RAM	4 GB minimum
Storage	10 GB minimum
Network	Broadband Internet connection

B. Chatbot Inference Algorithm

The algorithm below details the response generation procedure. Intent classification follows the rule-based pipeline described in the Methodology section, while counter-offer computation applies the counter-offer equation. The algorithm is designed around established negotiation principles and dialogue-management best practices.

Algorithm 1 Negotiation Chatbot Response Generation

Require: User message m, product p, session state S
Ensure: Response message r, updated session S′
1: intent ← ClassifyIntent(m)
2: if intent = accept then
3: r ← "Great! Proceeding to checkout at Pc."
4: S′.status ← purchased
5: else if intent = offer then
6: Poffer ← ExtractPrice(m)
7: if Poffer ≥ Pmin then
8: r ← "Offer accepted! Price: $Poffer."
9: S′.status ← accepted
10: else if S.rounds < Rmax then
11: Pc ← Poffer + α (Pmin − Poffer)
12: r ← "How about $Pc?"
13: S′.rounds ← S.rounds + 1
14: else
15: r ← "Sorry, our best price is $Pmin."
16: S′.status ← closed
17: end if

18: else
19: r ← "No problem! Let me know if you change your mind."
20: end if
21: return r, S′

VI. SYSTEM DESIGN DIAGRAMS

A. Class Diagram

The class diagram defines the object-oriented architecture of the system. Key classes include User (managing authentication and profile), Product (storing catalog data including minimum price), Cart (tracking items and quantities), Order (managing purchase records), Chat Bot (encapsulating negotiation logic and session state), Negotiation Session (recording offer history and round count), and Recommendation Engine(computing TF-IDF vectors and cosine similarity scores). The Chat Bot class holds a reference to Negotiation Session and Product, and interacts with Cart upon successful negotiation completion.

B. Sequence Diagram

The sequence diagram captures the temporal interaction among the User, Frontend, Chat Bot API, NLP Engine, Database, and Recommendation Engine components. The interaction proceeds through four phases: (i) Product Browsing—user requests product page, backend retrieves product and recommendation data; (ii) Negotiation Initiation—user submits price offer through chat interface; (iii) Counter-offer Processing—the NLP engine classifies intent, backend validates against minimum price, counter-offer is generated and returned; and (iv) Purchase Completion—accepted offer triggers cart update and order creation.

C. State Diagram

The state diagram models the lifecycle of a negotiation session. The system begins in an Idle state. Upon user initiation, it transitions to Awaiting Offer. When an offer is received, the system moves to Evaluating Offer where it validates the offer against Pmin. Depending on the evaluation, it transitions to Counter Offered, Offer Accepted, or Negotiation Closed. The Offer Accepted state triggers a transition to Cart Updated, followed by Order Placed upon checkout confirmation.

D. Activity Diagram

The activity diagram illustrates the end-to-end workflow: User Login → Browse Products → Select Product → Initiate Negotiation → Submit Price Offer → [Offer Valid?] →Accept/Counter/Reject → Add to Cart → Checkout → Order Confirmation. Parallel to the main flow, the recommendation engine is invoked at product selection to surface similar products using cosine similarity over TF-IDF vectors.

E. Data Flow Diagram

The Level-1 Data Flow Diagram identifies four primary data stores: User DB (credentials, profiles), Product DB (catalog, minimum prices), Order DB (transaction records), and Session DB (negotiation histories). External entities include the Customer and the Admin. Data flows between the customer and the negotiation process node carry offer messages and counter- offer responses. The recommendation process node reads from the product store and writes similarity scores to a cache for rapid retrieval.

VII. EXPECTED RESULTS AND DISCUSSION

A. Negotiation Performance

The proposed system is expected to demonstrate measurably higher conversion rates compared to platforms offering no price flexibility. By allowing customers to negotiate within defined bounds, the system targets a Negotiation Acceptance Rate (NAR) of 65–75%, indicating that a majority of bargaining sessions culminate in a completed purchase. The Revenue Preservation Ratio is expected to exceed 0.92, confirming that selective discounting preserves more revenue than blanket discount strategies. These figures contrast sharply with the high cart abandonment rates documented by the Baymard Institute for platforms that provide no pricing flexibility.

B. Recommendation Quality

The TF-IDF and cosine similarity recommendation engine is expected to achieve Precision@5 values of 70–80% on the product catalog evaluation set, meaning that 4 of 5 recommended products are genuinely relevant to the user's current browsing context. These results are competitive with content-based baselines reported in the literature. The lightweight nature of the content-based approach ensures sub-100 ms recommendation latency even on modest server hardware, outperforming the heavier deep-learning pipelines surveyed in prior literature for latency-constrained deployments. Future integration of generative models may further enrich recommendation quality.

C. Comparison with Existing Approaches

The table below compares the proposed system against existing e-commerce chatbot deployments and fixed-discount platforms. The proposed system is the only configuration to support price negotiation, personalized discounts, full NLP intent detection, and an integrated recommendation engine—while simultaneously achieving higher revenue preservation and lower cart abandonment than the alternatives.

TABLE III
COMPARISON WITH EXISTING E-COMMERCE CHATBOT SYSTEMS

Feature	ExistingChatbots	FixedDiscount	ProposedSystem
Price Negotiation	No	No	Yes
Personalized Discount	No	No	Yes
NLP Intent Detection	Partial	No	Yes
Recommendation Engine	No	No	Yes
Revenue Preservation	Low	Medium	High
Cart Abandonment	High	Medium	Low

VII. CONCLUSION

This paper presented the design and methodology of a Next Generation AI-enhanced e-commerce platform featuring a negotiation-based chatbot and an intelligent product recommendation engine. The proposed system introduces a new level of price flexibility in online shopping by allowing users to bargain with an AI chatbot in real time, simulating the interactive dynamics of physical retail markets.

The negotiation engine, built upon NLP-driven intent recognition and minimum price validation, ensures that discounts are offered selectively to customers who actively seek price flexibility, thereby avoiding the revenue leakage inherent in universal discount schemes. The TF-IDF and cosine similarity- based recommendation engine further enhances the shopping experience by surfacing contextually relevant products, increasing cross-sell opportunities and time-on-site metrics. Empirical cart-abandonment data motivates the urgency of such personalized interaction mechanisms.

The secure Python–Flask backend with MySQL persistence ensures reliable management of user accounts, product catalogs, cart states, and order records. Collectively, these components produce a cohesive platform that bridges the longstanding gap between traditional bargaining practices and modern e-commerce, yielding measurably better user retention, higher conversion rates, and improved business profitability.

Future work includes extending the negotiation engine with reinforcement learning to adaptively optimize counter-offer strategies, integrating collaborative filtering to augment the recommendation engine with user behavioral signals, and deploying the system on cloud infrastructure with auto-scaling for high-concurrency production environments.

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