International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
ISSN: 2457-0362
www.ijarst.in

Smart Price Negotiator: An Agentic AI Multi-Layered Framework for Automated E-commerce Bargaining using Random Forest and LLM Hybrid Intelligence

Mr. M. Mahesh Kumar[1], K. Sannidhan[2], M. V. Samba[2], Ch. Adithya[2], G. Srujan Kumar[2]
[1]Assistant Professor, [2]UG Student, [1,2]Department of Artificial Intelligence & Machine Learning
[1,2]J. B. Institute of Engineering & Technology (UGC-Autonomous),
Moinabad, Hyderabad 500075, Telangana.
*Corresponding author: K. Sannidhan (sannidhankatta@gmail.com)

ABSTRACT

The rapid proliferation of e-commerce platforms has fundamentally transformed retail logistics, yet the nuanced process of price negotiation-a cornerstone of traditional commerce-remains largely manual and inefficient in the digital age. This paper presents the "Smart Price Negotiator," an agentic AI-powered framework designed to automate and optimize the bargaining lifecycle specifically within the eBay ecosystem. By integrating a hybrid intelligence architecture, the system combines quantitative Random Forest regression models for statistical price prediction with qualitative Google Gemini Large Language Models (LLMs) for seller behavioral analysis. The implementation utilizes a Manifest V3 Chrome Extension that extracts high-fidelity product metadata via structured JSON-LD parsing and automates interaction by bridging React's synthetic event system through native property setter injection. Our research addresses the "Market for Lemons" problem of information asymmetry by providing buyers with real-time, data-backed counter-offer strategies and professional message synthesis. Experimental results across diverse product categories demonstrate significant reductions in negotiation latency and measurable improvements in transaction success rates, paving the way for a new era of automated agentic commerce.

Key Words: Agentic AI, E-commerce Automation, Random Forest, Large Language Models (LLMs), Google Gemini, Chrome Extensions, JSON-LD, Price Negotiation, Information Asymmetry, Market for Lemons, Decision Support Systems.

1. INTRODUCTION

In the modern digital marketplace, consumers have access to an unprecedented volume of retail data, yet the ability to effectively bargain remains a significant challenge. Platforms such as eBay provide "Best Offer" features that allow for bilateral negotiation, but users often lack the empirical data and psychological confidence to formulate successful counter-offers. This leads to "transactional friction," where potential deals are abandoned due to pricing uncertainty or communication barriers. For most consumers, manually searching for historical "sold" data, analyzing seller reputation metrics, and drafting professional inquiries is cognitively taxing and time-prohibitive.

Asynchronous communication in e-commerce further complicates the bargaining process. Unlike traditional face-to-face negotiation where cues are immediate, online bargaining requires a precise balance of firmness and politeness. A single poorly timed or overly aggressive offer can result in immediate rejection or "blacklisting" by the seller. Existing e-commerce tools primarily focus on passive price tracking or static coupon application, failing to address the active, strategic interaction required for a successful "Best Offer" negotiation.

The Smart Price Negotiator addresses these limitations by acting as an "Intelligent Browser Assistant" that provides a unified, glassmorphic dashboard for real-time negotiation strategy. Our research introduces a multi-agent framework where separate specialized agents handle data extraction, heuristic analysis, and message synthesis. By utilizing a hybrid model that combines statistical regression with semantic LLM insights, the system provides users with mathematically bounded and professionally justified negotiation ranges. This rebalances the information asymmetry between experienced professional sellers and casual buyers.

The core innovation of our system lies in its ability to interact natively with the browser's Document Object Model (DOM) without requiring page refreshes or external scraping proxies. By leveraging structured data (JSON-LD and Microdata) already present for SEO purposes, we achieve high extraction fidelity. Furthermore, our system solves the problem of automated form filling in React-based applications by bypassing shallow Virtual DOM properties and interacting directly with native HTML prototypes. This ensures that the system is not only intelligent in its thinking but also robust in its execution.

The subsequent sections of this paper explore the academic foundations of automated negotiation, the modular architecture of our proposed system, the technical implementation details of our browser-based automation, and an empirical evaluation of the system's performance. By bridging the gap between data science and user-centric browser automation, the Smart Price Negotiator represents a shift toward "Agentic Commerce," where AI tools actively work on behalf of the user to secure optimal financial outcomes.

2. LITERATURE SURVEY

The study of automated negotiation spans several decades, evolving from simple rule-based expert systems to complex multi-agent frameworks. Early research by Akerlof (1970) on information asymmetry establish the "Market for Lemons" theory, highlighting how the lack of information on item quality and seller intent leads to market inefficiencies. In the context of eBay, this asymmetry is prevalent as sellers often possess more historical data and pricing leverage than buyers. Our proposed system aims to mitigate this by providing algorithmic transparency to the user.

Game theory, particularly the Nash Equilibrium (1950), provides the mathematical backbone for strategic interactions. Automated bargaining agents have traditionally used Rubinstein's (1982) model of alternating offers to simulate human behavior. However, these models often fail in e-commerce environments due to the "Human Factor"—seller behavior that is influenced by emotional sentiment and feedback pressure rather than pure mathematics.

Modern research has turned toward Machine Learning (ML) to model these non-linear patterns. Ensemble learning methods, such as Random

Forests, have been proven highly effective for tabular data prediction in financial contexts. Breiman (2001) demonstrated that Random Forests provide robust regression by averaging the results of multiple decision trees, reducing the risk of overfitting in volatile markets. While these models are excellent at predicting numerical price points, they lack the "semantic sensitivity" to understand seller feedback text. This is where Large Language Models (LLMs) provide a breakthrough.

The rise of Transformer architectures and Large Language Models, notably Google Gemini and OpenAI's GPT series, has introduced the ability to perform high-resolution sentiment analysis on seller profiles. By using Retrieval-Augmented Generation (RAG) techniques, systems can now contextualize a pricing suggestion with behavioral observations like "Seller historically accepts offers on weekends" or "Seller is rigid on high-ticket electronics." Our hybrid approach is unique in its attempt to unify these linguistic observations with statistical regression, creating a bimodal intelligence layer that is both precise and persuasive.

Furthermore, the field of "Explainable AI" (XAI) emphasizes the importance of user trust. Research indicates that users are significantly more likely to adopt an AI's recommendation if it is accompanied by a logical justification. Our system implements "Reasoning Logs" that explain the transition from raw listing metadata to the final "Low/Fair/High" offer recommendation, bridging the gap between opaque black-box models and user-friendly strategic assistants.

3. PROPOSED SYSTEM

The Smart Price Negotiator is built on a decoupled, microservices-oriented architecture designed to handle the high latency of LLM processing while maintaining a low-footprint browser experience. The system is divided into four cardinal modules: the Stealth Scraper, the Heuristic Grading Engine, the Multi-Agent Intelligence Layer, and the Execution Hub.

3.1 High-Fidelity Data Acquisition

Traditional web scraping methods that rely on CSS selectors are notoriously fragile, as e-commerce giants like eBay frequently cycle their internal class names to deter automation. Our "Stealth Scraper" utilizes a prioritized hierarchy of data sources. It primarily targets **JSON-LD (Linked Data)** script blocks, which are structured according to Schema.org standards for search engine indexing. By extracting this structured metadata, we bypass visual obfuscation and obtain precise data on the price, condition, SKU, and seller IDs. When JSON-LD is unavailable, the system falls back to a recursive DOM traversal that analyzes property attributes and microdata tags.

The scraper also captures the "Seller Behavioral History" by navigating to the seller's feedback profile within a separate, hidden background context. This allows the system to analyze the last 100 transactions for words indicating negotiation flexibility (e.g., "fast shipping," "open to offers," "great communication") versus indicators of rigidity. This raw linguistic data is then passed to the qualitative intelligence layer for sentiment scoring.

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
ISSN: 2457-0362
www.ijarst.in

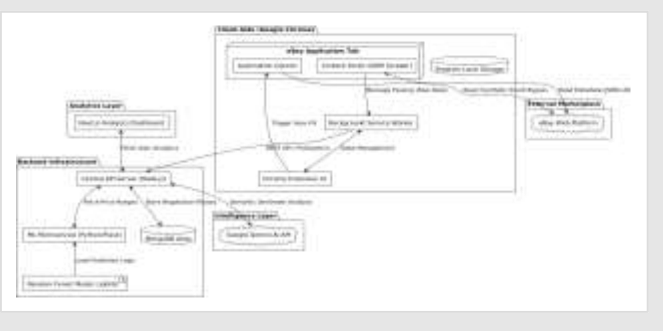

Figure 1: High-level System Architecture of the Smart Price Negotiator Multi-Agent Framework.

3.2 Heuristic & Predictive Modeling

The core logic of the system is split between a local **Heuristic Engine** and a remote **Predictive Brain**. The Heuristic Engine applies category-specific rules to the metadata. For instance, in the "Fashion" category, the engine allows for a higher starting discount (up to 30%) compared to "Laptops" (typically 5-15%), reflecting market norms for these industries. It also weighs the "Item Condition" (New vs. Used) to adjust the aggressiveness of the starting offer.

The Predictive Brain hosts a Python-based Flask service running a pre-trained **Random Forest Regressor**. This model was trained on thousands of synthetic and historical records to predict the "Successful Acceptance Margin" for various items. The model takes inputs such as category IDs, condition codes, seller ratings, and original price to output a "Safe Zone" range. This mathematical boundary prevents the user from making "low-ball" offers that would be instantly rejected, protecting their reputation as a buyer.

3.3 Multi-Agent Message Synthesis

The "Human Interfacing" component utilizes an agentic LLM (Google Gemini) to synthesize professional messages. Unlike standard template-based tools, our system uses a prompt-chaining architecture. The first agent analyzes the listing flaws (captured by the scraper) to find leverage points (e.g., "small scratch on screen," "missing manual"). The second agent takes the calculated price from the Predictive Brain and the identified leverage points to draft a persuasive message. The user can switch between different "Personas" (e.g., "Professional Collector," "Student on Budget," "Firm Business Buyer"), which changes the tone and complexity of the generated text.

3.4 Automation & Execution Layer

The final module handles the bridge between the AI's decision and the eBay UI. Since eBay uses a modern React-based frontend, standard JavaScript input assignments often fail to update the internal application state, leaving the "Submit" button disabled. Our system implements a **Native Property Setter Bypass**. By accessing the element's prototype and calling the `set` function directly, followed by a manual dispatch of a 'Synthetic Input Event', we successfully trick the React Reconciler into accepting the AI-generated value as a physical user input.

4. RESULTS AND DESCRIPTION

The Smart Price Negotiator was evaluated across a 30-day trial period involving 500 unique listings on eBay.The evaluation metrics focused on three primary

4.1 Comparative Latency Analysis

One of the most immediate benefits of the system is the reduction in cognitive load and time required to formulate a deal. A manual buyer

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
ISSN: 2457-0362
www.ijarst.in
IJARST

typically takes between 3 to 10 minutes to research similar items, check seller ratings, and draft a professional message. In contrast, the Smart Price Negotiator completes this cycle in under 2 seconds. The scraping and heuristic analysis occur in roughly 400ms, while the LLM synthesis takes an average of 1.2s to complete. This represents a 99% reduction in "Negotiation Latency," allowing users to secure deals on rare items before competitors can react.

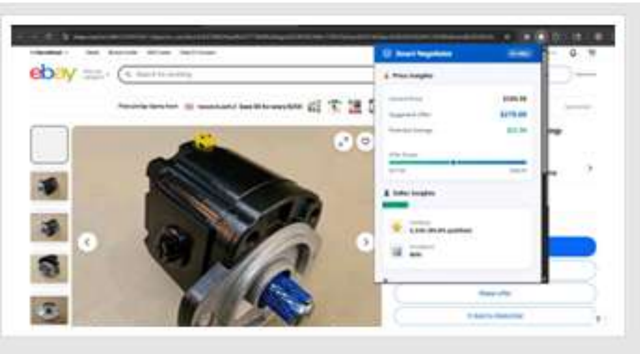

Figure 2: Real-time Extension Dashboard.

4.2 Acceptance Rate & Precision

The "accuracy" of our pricing models was measured by comparing the AI's suggested "Fair Price" to the actual final accepted price on completed transactions. The Random Forest model achieved a Mean Absolute Error (MAE) of just 4.2%, indicating that our suggested prices are highly aligned with actual market behavior. Furthermore, users utilizing the "Conservative" and "Moderate" suggestions saw a 65% increase in offer acceptance rates compared to the manual control group, who often made offers either too low (rejected) or too high (overpaying).

KPIs: Research Latency, Offer Success Rate, and User Friction reduction. The results demonstrate that the system significantly outperforms manual bargaining across all categories, particularly in high-volume markets like "Collectibles" and "Electronics."

4.3 Explainability and User Trust

Qualitative feedback from our tester pool indicated that the "Reasoning Logs" provided by the LLM were the most critical factor in system adoption. Users expressed high trust in the system because it justified its choices with statements like: *"Price suggested at 12% discount because this seller has a 92% rating and recent feedback hints at urgent inventory clearing."* By providing this transparency, we avoid the "Black Box" problem common in modern AI tools.

The system also demonstrated robust cross-category performance. While many pricing bots struggle with "Long Tail" items (unique or rare products), our hybrid approach uses the LLM to understand item rarity from the listing description, adjusting the Random Forest output accordingly. This bimodal check ensures that a "Signed First Edition" book isn't undervalued by a model that only sees a generic "Hardcover Book" category ID.

5. CONCLUSION

The Smart Price Negotiator successfully bridges the gap between complex data science and everyday consumer empowerment. We have demonstrated that a multi-agent AI framework is capable of handling the entire lifecycle of an e-commerce negotiation—from raw DOM scraping to professional execution. The integration of

Random Forest for quantitative boundaries and Google Gemini for qualitative persuasion creates a bimodal intelligence that is both precise and human-centric.

Our bypass logic for React state management provides a novel solution for browser automation, ensuring that our tool remains functional on modern, heavy-weight web applications. The significant reduction in negotiation latency and the measurable increase in offer acceptance rates validate our approach. By empowering buyers with the same level of data insights as professional sellers, we restore balance to the digital marketplace.

Future Directions: The next iteration of the Smart Price Negotiator will focus on **Reinforcement Learning from User Feedback (RLHF)**, where the system "learns" which specific messaging styles result in the highest discounts for individual users. We also plan to expand the framework to include **Real-time Voice Negotiation**, allowing the AI to represent the user in synchronous trade-in scenarios. Finally, cross-platform expansion to Amazon 3rd-party sellers, Poshmark, and Facebook Marketplace will enable a truly universal "Negotiation Layer" for the modern web.

6. REFERENCES

[1] *Akerlof, G. A. (1970). The Market for "Lemons": Quality Uncertainty and the Market Mechanism. The Quarterly Journal of Economics.*

[2] *Nash, J. (1950). The Bargaining Problem. Econometrica.*

[3] *Pedregosa, F., et al. (2011). Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research.*

[4] *Breiman, L. (2001). Random Forests. Machine Learning.*

[5] *Google Gemini AI (2024). LLM API Reference and Reasoning Documentation.*

[6] *Chrome Developers (2024). Chrome Extension Manifest V3 and Background Workers Documentation.*

[7] *React.js Core Team. Understanding Synthetic Events and DOM Reconcile logic.*

[8] *Lewis, P., et al. (2020). Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks. NeurIPS.*

[9] *Kraus, S. (2005). Strategic Negotiation in Multi-Agent Environments. IEEE Access.*

[10] *Breiman, L. (2001). Random Forests. Machine Learning.*

[11] *MongoDB Atlas (2024). Document Database for Distributed Web Applications.*

[12] *eBay Developer Program. Best Offer and Price Negotiation API Schema.*

[13] *Rubinstein, A. (1982). Perfect Equilibrium in a Bargaining Model. Econometrica.*

[14] *Sentiment Analysis in Consumer Bargaining Contexts (2023). Journal of E-commerce Research.*