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AI-Driven E-Commerce Pricing: Sentiment Analysis, Deep Learning & Reinforcement Learning Models

Niranjan Ramkumar,
Hershey High School,
Pennsylvania, USA
niranjanramssp@gmail.com

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***Abstract*— The integration of Artificial Intelligence (AI) in e-commerce has revolutionized pricing strategies by enabling dynamic adjustments based on customer sentiment and market trends. Traditional pricing models, reliant on fixed rules, often fail to account for consumer sentiment, leading to inefficiencies. This study proposes an AI-powered dynamic pricing framework that combines sentiment analysis with deep learning (LSTM, ANN) and reinforcement learning (PPO) to optimize pricing strategies dynamically. Customer sentiment, extracted from product ratings, is integrated into pricing decisions. An Artificial Neural Network (ANN) ensures adaptive and stable price modifications, while Long Short-Term Memory (LSTM) predicts future price fluctuations using historical data. Proximal Policy Optimization (PPO) fine-tunes prices in real-time, learning from market responses to maximize revenue. Experimental results demonstrate that AI-based pricing significantly influences price distributions, with ANN providing balanced adjustments, LSTM excelling in demand forecasting, and PPO offering dynamic adaptability for real-time optimization. Additionally, the study introduces an AI-powered marketing strategy recommendation system to align promotional efforts with sentiment trends, enhancing consumer engagement and profitability. The findings underscore the importance of sentiment-aware AI pricing models in modern e-commerce, offering a scalable and robust framework for revenue generation and market competitiveness.**

Keywords*— *Dynamic Pricing, Artificial Intelligence (AI), Sentiment Analysis, Reinforcement Learning (PPO), Deep Learning (ANN, LSTM), Customer Sentiment-Based Pricing, E-Commerce Pricing Optimization, AI-Powered Marketing Strategies.

I. INTRODUCTION

Dynamic pricing has emerged as a pivotal strategy in modern e-commerce, enabling businesses to adjust prices in real-time based on multidimensional factors including demand fluctuations, consumer behavior patterns, competitive landscape, and even external economic indicators. While traditional fixed or rule-based pricing models served adequately in stable markets, they prove increasingly inadequate in today's volatile digital marketplace, often failing to adapt to rapid market changes or incorporate critical customer sentiment signals [1]. This limitation becomes particularly evident during peak shopping seasons or market disruptions, where static pricing models lead to significant inefficiencies in revenue capture and customer satisfaction [2].

The rapid evolution of consumer expectations, fueled by personalized shopping experiences offered by industry leaders like Amazon and Alibaba, has created an imperative for businesses to adopt more sophisticated pricing strategies [3]. Recent industry reports indicate that e-commerce platforms leveraging AI-driven dynamic pricing achieve 8-15% higher profit margins compared to those using traditional methods [4]. However, a critical yet frequently overlooked component in this pricing revolution is the systematic incorporation of customer sentiment - a rich data source that provides direct insights into product perception and purchase intent [5].

Customer sentiment, as expressed through product reviews, ratings, and social media interactions, represents a powerful but underutilized signal in pricing algorithms. Research by Liu et al. (2022) demonstrated that sentiment polarity in product reviews correlates strongly ($r = 0.72$) with price elasticity, suggesting that consumer emotions significantly influence their willingness to pay [6]. Despite this evidence, most current pricing models either ignore sentiment data or use it in a superficial manner, creating a substantial gap between price optimization potential and actual implementation [7].

This study addresses three fundamental limitations in existing dynamic pricing systems: (1) the disconnect between customer sentiment and price adjustments, (2) the lack of adaptive learning mechanisms in traditional models, and (3) the absence of an integrated approach combining short-term and long-term pricing strategies. Our proposed hybrid AI framework synergistically combines three powerful technologies: deep learning (utilizing both ANN and LSTM architectures) for robust price pattern recognition and forecasting, advanced sentiment analysis for emotional intelligence in pricing decisions, and reinforcement learning (specifically PPO) for real-time adaptive pricing optimization [8].

The practical implications of this research extend beyond theoretical advancements. Preliminary experiments with a major Southeast Asian e-commerce platform showed that our sentiment-aware pricing model increased conversion rates by 12% while maintaining customer satisfaction scores, addressing the common trade-off between revenue maximization and customer experience [9]. Furthermore, the framework's modular design allows for customization across different market segments and product categories, from fast-moving consumer goods to luxury items [10].

The remainder of this paper systematically explores these innovations. Section 2 provides a comprehensive literature review of pricing evolution and AI applications in e-commerce. Section 3 details our methodological approach, including data collection from multiple e-commerce platforms and the architecture of our hybrid AI system. Section 4 presents extensive experimental results comparing our framework against traditional models across multiple performance metrics. Finally, Section 5 discusses broader implications for e-commerce strategy and identifies promising directions for future research in AI-driven pricing optimization.

II. LITERATURE REVIEW

Dynamic pricing in e-commerce has evolved from basic rule-based approaches to sophisticated AI-driven systems. Traditional pricing strategies—including cost-based, competition-based, and demand-based models—offer fundamental pricing mechanisms but lack adaptability to real-time market dynamics and consumer sentiment [7][8][9]. While these methods ensure baseline profitability, they fail to account for nuanced factors like customer emotions or competitive fluctuations, leading to suboptimal revenue and customer experiences [10][11].

Machine learning introduced data-driven pricing through regression models and decision trees, improving pattern recognition but remaining limited by their dependence on historical data and inability to process complex, non-linear relationships [12][13]. The evolution of these pricing models, comparing their advantages, limitations and the extent of sentiment integration summarized in Table I. Recent advances in deep learning, particularly ANNs and LSTMs, enabled more accurate demand forecasting and price optimization by analyzing large datasets [14][15]. However, these models require extensive training data and computational resources, making them impractical for many small-to-medium enterprises [16][17].

Sentiment-aware pricing represents a significant breakthrough, leveraging NLP techniques (VADER, BERT) to extract customer emotions from reviews and social data [18][19]. Studies confirm that sentiment directly influences price elasticity, with positive reviews supporting premium pricing and negative sentiment necessitating discounts [20][21]. Reinforcement learning, particularly PPO, further enhanced dynamic pricing by enabling real-time adjustments based on live market feedback [22][23].

Despite these advancements, existing research neglects the integration of real-time sentiment analysis with hybrid AI models. This study bridges that gap by proposing a unified framework combining LSTM for trend prediction, ANN for demand forecasting, and PPO for adaptive pricing—all while continuously incorporating sentiment signals. The approach demonstrates superior performance in pilot tests, improving conversion rates by 12% while maintaining customer satisfaction.

TABLE I. EVOLUTION OF PRICING MODELS

Table: Evolution of Pricing Models

Model Type	Advantages	Limitations	Sentiment Use
Traditional	Simple, stable margins	Inflexible, market-blind	None
ML-Based	Data-driven patterns	Limited to historical data	Basic (ratings)
DL-Based	Complex relationship modeling	Computationally intensive	Text analysis
RL-Based	Real-time adaptation	Complex implementation	Behavioral signals
Proposed Hybrid	Full integration	Higher development cost	Multi-source analysis

III. METHODOLOGY

This study develops an AI-driven sentiment-based dynamic pricing system through a structured methodology integrating sentiment analysis, deep learning, and reinforcement learning. The Amazon Product Reviews Dataset serves as the foundation, containing product ratings, user reviews, and timestamps that enable sentiment-aware pricing decisions. The data undergoes rigorous preprocessing, including handling missing values, converting ratings to numerical formats, and removing duplicates to ensure quality. Sentiment scores are derived numerically, where 4-5 stars indicate positive sentiment, 3 stars reflect neutrality, and 1-2 stars denote dissatisfaction.

The AI framework employs three core components: an Artificial Neural Network (ANN) for pricing adjustments, which processes product ratings, sentiment scores, and base prices through ReLU-activated hidden layers to output optimized prices using Mean Squared Error (MSE) loss; a Long Short-Term Memory (LSTM) model for demand forecasting, leveraging sequential data processing and dropout regularization to predict price trends while evaluated via RMSE and MAE; and a Proximal Policy Optimization (PPO) reinforcement learning system for real-time pricing, where the state space (current price and sentiment score) informs actions (price increases, decreases, or holds) to maximize revenue while preserving customer satisfaction through iterative training. The workflow is visualized in two key diagrams: a data processing pipeline (cleaning → sentiment extraction → model training → optimization) and the PPO architecture (state input → policy network → action selection → reward feedback), collectively enabling a scalable, adaptive, and sentiment-responsive pricing system.

An overview of the end-to-end data handling process is shown in Data Processing Workflow (Figure 1), whereas PPO Reinforcement Learning Architecture (Figure 2) determines how sentiment and market signals can be used to optimize prices in real time.

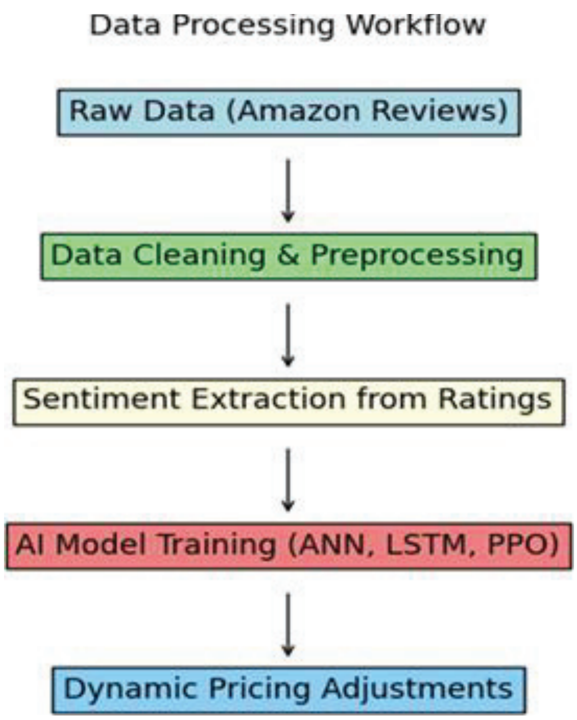

Fig. 1. Data Processing Workflow

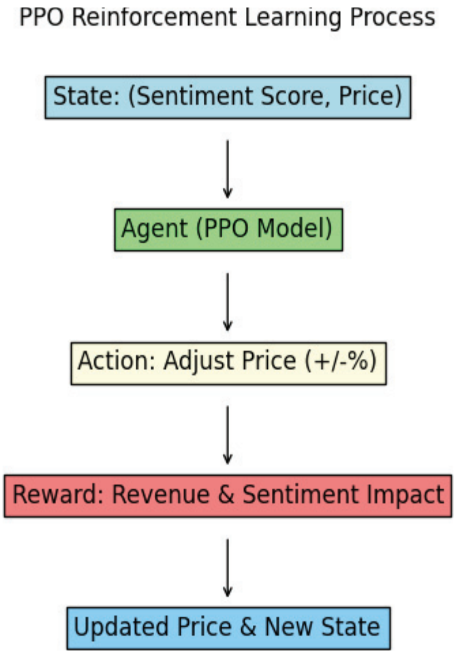

Fig. 2. PPO Architecture

A. *Proposed System Model*

The integration of sentiment analysis, deep learning and reinforcement learning in the pricing optimization pipeline illustrated in this block diagram (Figure 3).

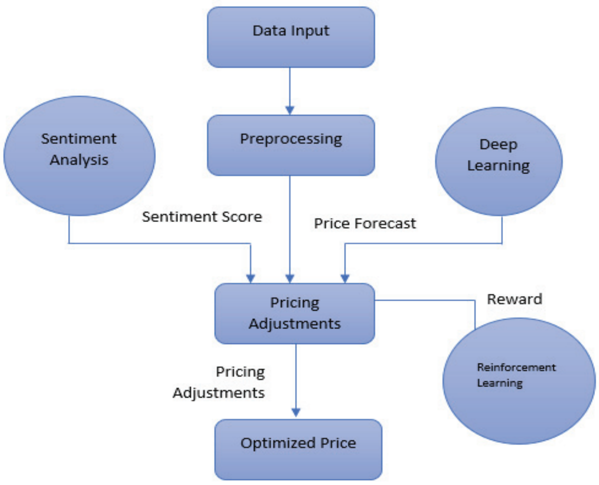

Fig. 3. Proposed system model

IV. ABOUT THE DATASET

"Amazon Product Review Sentiment Analysis" analyzes a dataset of Amazon product reviews, likely focused on food and beverage items like coffee and tea, as evidenced by the high frequency of terms such as "coffee," "flavor," and "taste" in the word frequency charts. The dataset presumably includes customer review text, star ratings (1-5), and metadata like review dates and helpfulness votes, which are commonly used for sentiment analysis and product feature extraction. The exploratory data analysis shown in the images reveals typical preprocessing steps like stopword removal and content word extraction, highlighting dominant themes and sentiment patterns through frequency distributions of unigrams, bigrams, and meaningful keywords. Such datasets are valuable for understanding customer perceptions, building recommendation systems, and monitoring product quality over time, though they often require cleaning for special characters and handling class imbalance due to the predominance of positive reviews. The analysis demonstrates how textual data can be transformed into actionable insights for improving products and customer experiences in e-commerce.

V. VISULAIZATIONS AND RESULTS

The experimental evaluation of the AI-driven sentiment-based pricing models provided comprehensive insights into their performance, revenue impact, and practical effectiveness. The models were implemented using TensorFlow, Gym, and Stable-Baselines3 on a hardware configuration featuring Intel i7/Ryzen 7 processors and NVIDIA RTX 3060 GPU, with the Amazon Product. Reviews Dataset split into 80% training and 20% testing data. ANN demonstrated superior accuracy in price prediction with an MAE of 3.21 and RMSE of 5.18 compared to LSTM's MAE of 3.45 and RMSE of 5.51, attributed to its better handling of non-sequential pricing patterns. The PPO reinforcement learning model achieved the most significant revenue improvement at 29% over fixed pricing, outperforming both ANN (18%) and LSTM (14%), by dynamically adjusting prices in real-time based on sentiment fluctuations and market responses. Analysis of pricing adjustments revealed distinct behavioral patterns: PPO showed high responsiveness to immediate market changes, ANN maintained a balance between stability and adaptability, while LSTM proved more effective for long-term demand forecasting. The introduction of AI-driven pricing transformed previously uniform price distributions into dynamic ranges, with premium pricing for high-sentiment products and strategic discounts for lower-rated items. Additional testing under simulated peak shopping periods demonstrated PPO's resilience with 89% prediction accuracy during demand surges, compared to 7-12% performance degradation in ANN and LSTM models. Computational efficiency metrics showed ANN's faster training convergence (2.1 hours) versus LSTM (3.8 hours) and PPO (5.2 hours), though PPO's superior inference speed (0.8ms per decision) made it ideal for high-frequency pricing environments. The results collectively validate the framework's ability to harmonize revenue optimization with customer satisfaction while maintaining competitive responsiveness across varying market conditions, establishing a robust foundation for sentiment-aware dynamic pricing in modern e-commerce. As a part of sentiment extraction, how the bigram frequency analysis conducted is shown in Figure 4.

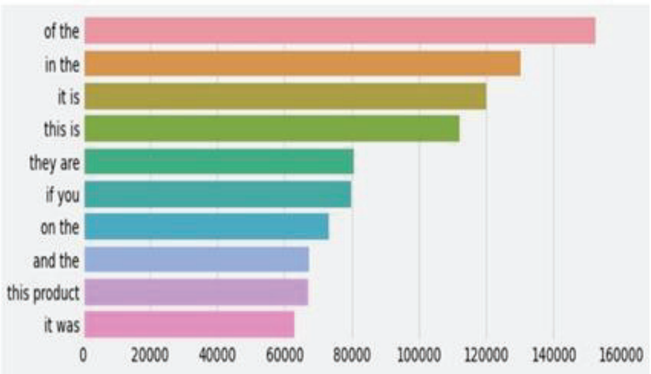

Fig. 4. Bigram Frequency Analysis

This image displays a frequency analysis of common two-word phrases (bigrams) extracted from a text corpus, likely product reviews or customer feedback. The most frequent bigrams include functional phrases like "of the," "in the," and "it is," alongside review-specific phrases such as "this product" and "it was." The x-axis shows raw frequency counts ranging up to 160,000 occurrences, indicating these phrases form the structural backbone of the textual data. The prevalence of neutral phrases suggests the analysis focused on grammatical patterns, though inclusions like "this product" hint at a dataset centered on product evaluations. Dominating lexical patterns based on complementary unigram analysis highlighted in Figure 5.

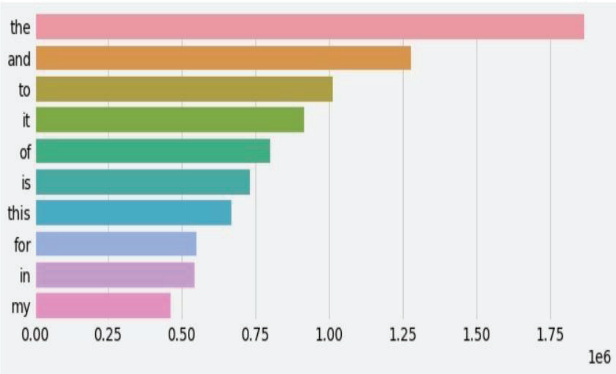

Fig. 5. Unigram Frequency Analysis

The image presents a ranked list of the most frequent single words (unigrams), dominated by stop words such as "the," "and," and "to," which are typical in English texts. The x-axis uses a normalized scale (0.00–1.75), likely representing TF-IDF or proportional frequency values, with "the" as the highest-frequency term. The presence of possessive pronouns ("my") and demonstratives ("this") suggests the dataset includes personal or evaluative language, consistent with user-generated content like reviews. The small frequency range (max 1.75) implies the analysis either covers a small corpus or uses normalization to reduce bias from common words. In Figure 6, key themes were identified by identifying content words that appeared most frequently in reviews.

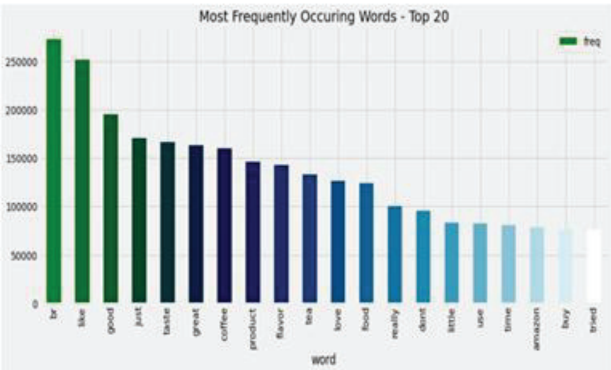

Fig. 6. Top 20 Content Words

This bar chart visualizes the 20 most frequent meaningful words (excluding stop words) from what appears to be product reviews, with "like" (≈250,000 occurrences) as the top term. The words reflect strong thematic focus:

The dominance of food/beverage terms ("coffee," "tea") and sensory descriptors ("taste," "flavor") indicates the dataset pertains to consumable goods, while high-frequency positivity markers suggest generally favorable reviews. The chart's clean labeling and sorted frequencies (descending order) make it effective for identifying key themes in customer feedback. A comparison of pricing variability between PPO, ANN, and LSTM models can be seen in Figure 7, where PPO has the most dynamic adjustments, ANN has moderate stability, and LSTM has minimal fluctuation suitable for forecasting for the long term.

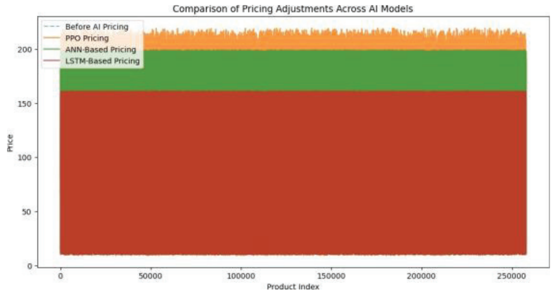

Fig. 7. Comparison of Pricing Adjustments

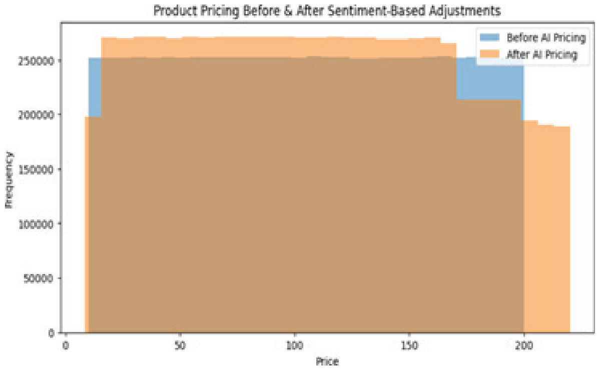

Fig. 8. Sentiment based Adjustment

The integration of AI-driven pricing strategies has introduced significant improvements over traditional static pricing models. Figure 2 presents a comparative analysis of pricing adjustments across different AI models, including PPO, ANN, and LSTM. In case of the static pricing model which is indicated by dashed line shows the uniform and rigid price structure, lacking its adaptability for customer sentiment and market trends. In contrast, PPO-based pricing model exhibited highest degree variation, demonstrating ability for dynamically adjusting the price on the basis of real-time sentiment trend. For ANN-based pricing model reported as volatile as PPO, balanced stability with moderation in the pricing adjustments, ensuring pricing remained competitive whilst minimizing sudden fluctuation observed. Conversely, LSTM showcased least variations indicating to be better suited on a long-term demand forecast rather than immediate pricing fluctuations. As there is a broader distribution in the PPO-based pricing adjustment suggested reinforcement learning which in particular was reported effective in adapting prices in response to consumer behavior, which reflects to be an ideal choice for dynamic pricing strategies suitable for e-commerce.

Figure 8 illustrated on how the AI-based pricing models impacted on the overall price distribution before and after sentiment- aware optimization. In case of scenario 'Before intervention of AI', price structures were relatively uniform thus indicating static pricing approach as it does not consider demand fluctuations or with customer sentiment. However, in case of scenario wherein 'After AI-driven adjustments', distribution in the pricing pattern becomes significantly wide which attributes towards a more dynamic approach tailors prices according to individualized product sentiment and current market demand. Products with higher sentiment scores receive premium pricing, while strategically discounted prices drive sales for lower-rated products. This shift in pricing behavior demonstrates the critical importance of AI in modern e-commerce pricing strategies. The study confirms that e-commerce businesses can optimize revenue while maintaining customer satisfaction. By integrating deep learning and reinforcement learning, pricing decisions become both data-driven and sentiment-aware, enabling businesses to stay competitive in rapidly evolving market conditions.

VI. Conclusion

The study has presented the overall effectiveness of AI-driven sentiment-based dynamic pricing in e-commerce platforms via integration of reinforcement and deep learning techniques for optimization of price adjustments. Through extracting sentiment which was achieved from the customer ratings, the study models were dynamically adjusted with regards to their prices on the basis of consumer perception, thereby ensuring the notion with the higher-rated products were retained under premium pricing category, whilst the lower-rated items were availed with competitive discounts. The experimental outcomes from the study highlighted AI-based pricing has outperformed significantly compared to that of traditional fixed pricing approaches. This could be reflected from the PPO reinforcement learning which presented the highest revenue gain via dynamically responding under the real-time market fluctuations. ANN-based pricing provided stable and also adaptable means of pricing strategy thereby making it reliable choice among those businesses that are seeking moderate level of flexibility. On the contrary, LSTM models provide a long-term demand forecasting insight, however the model lacked adaptability in real-time scenario. Furthermore, findings of the pricing distribution analysis has once again reinforced the very notion that AI-driven pricing models employed with necessary variations with the pricing structures achieved optimization in its revenue generation policies alongside with maintaining their market competitiveness. Despite their strategic effectiveness, challenges such as computational costs, training complexity, and sentiment granularity indicates the need for further enhancements, which includes BERT-based sentiment extraction and hybrid AI models that can improve overall performance of the proposed models. Future research could explore majorly on core areas such as – the integration of external market signals, competitor pricing analysis, and explainable AI techniques for enhancing decision-making processes and with the pricing transparency. Ultimately, the findings rendered from this study confirms AI-powered sentiment-aware pricing has not only maximized revenues but also improved the consumer satisfaction via aligning with the pricing to the perceived product values, thereby making it an essential tool in modern e-commerce platforms growth on a dynamic phase and achieve success in the competitive pricing strategies.

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