Department of MBA,
Sengunthar Engineering College
(Autonomous), Tiruchengode, India

Dr. Dure Najaf

Assistant Professor,
Economics and Business Studies Department,
Mazoon College, Sultanate of Oman

ISBN 978-81-988536-2-2

Imaginex Inks Publication

Published:22nd May 2025
Printed with care by Imaginex Inks Printing

https://www.imaginexinkspublication.com/

Contact Number : 9750663871
9962991057

E-COMMERCE
IL IN THE AI DRIVEN ERA

Editors

Dr. Sunantha.P

Dr. G. Yamuna

Dr. M. Sree Sakthivelan

Dr. Dure Najaf

Imaginex Inks Publication

The Future of E-Commerce Redefining Online and Retail in the AI-Driven Era

EDITORS

Dr. P. Sunantha

Associate Professor
Department of Commerce and Economics
Vels Institute of Science, Technology & Advanced Studies (VISTAS), Chennai

Dr. G.Yamuna

Assistant Professor
Department of Commerce
Dwaraka Doss Goverdhan Doss Vaishnav College, Chennai

Dr. M. Sree Sakthivelan

Professor & HOD
Department of MBA
Sengunthar Engineering College (Autonomous), Tiruchengode

Dr. Dure Najaf

Assistant Professor
Economics and Business Studies Department
Mazoon College, Sultanate of Oman

The Future of E-Commerce Redefining Online and Retail in the AI-Driven Era

Edited by

Dr.P.Sunantha, Dr. G.Yamuna, Dr. M. Sree Sakthivelan, Dr. Dure Najaf

Volume I June 2025

Price: Rs. 500/-

ISBN: 978-81-988536-2-2

Published by and copies can be had from:

Imaginex Inks Publication

2/158, Kurinji Nagar First St, Ponnan Nagar,

Irumbuliyur, Vandalur,

Chennai 600048, Tamil Nadu, India.

Phone: 9750663871, 9962991057

e-mail: imaginexinks@gmail.com

https://www.imaginexinkspublication.com/

ISBN: 978-81-988536-2-2

Chapter 6: Intelligent Pricing and Promotion Strategies in Conversational Commerce

Dr. Swathi Pradeepa[1]

[1]Assistant professor, Department of Commerce and Economics, Vels Institute of Science Technology and Advanced Studies (VISTAS), Chennai

---

The exponential growth of conversational commerce, propelled by the integration of AI-enabled voice and chat interfaces, has fundamentally redefined how brands interact with consumers. Beyond just facilitating search and purchase via natural language interfaces, these systems now influence strategic pricing and promotional decision-making, transforming static campaigns into dynamic, personalized experiences. As digital commerce continues to mature, intelligent pricing and promotion strategies are becoming pivotal in optimizing conversion rates, maximizing revenue, and enhancing customer retention (Shan 2025).

Traditionally, pricing strategies were determined through cost-plus models, rule-based segmentation, or periodic market analysis. Promotions, in turn, were planned through seasonal calendars and demographic assumptions. However, these conventional approaches often ignore real-time customer context, market volatility, and behavioral nuances. In contrast, modern conversational platforms powered by machine learning are capable of learning, adapting, and responding in real time. These advancements have ushered in a new paradigm where reinforcement learning, adaptive experimentation, and behavioral economics drive commercial outcomes (Jain and Kumar 2024).

The proliferation of AI-enabled commerce systems has catalyzed a fundamental shift in how pricing and promotions are designed, implemented, and optimized. Traditional price-setting and discounting mechanisms—often based on manual heuristics, rule-of-thumb margins, or batch-wise segmentation—are being rapidly displaced by **real-time, data-adaptive strategies** powered by reinforcement learning, experimental algorithms, and behavioral modeling.

6.1. Real-Time Price Optimization Using Reinforcement Learning

Modern retail environments are marked by dynamic demand patterns, volatile supply chains, and highly individualized customer behaviors. To remain competitive, retailers are increasingly implementing reinforcement learning for real-time price adjustments based on contextual data and observed outcomes (Powell et al.,2020).

Formulation as a Markov Decision Process (MDP)

Reinforcement learning models the pricing environment as an **MDP**, wherein:

ISBN: 978-81-988536-2-2

- States represent context vectors (e.g., time of day, competitor pricing, user segment, stock level)
- Actions are discrete or continuous price points
- Rewards are linked to conversion rates, profit margins, or customer lifetime value (CLV)
- Policies define the strategy for selecting the optimal price at each state

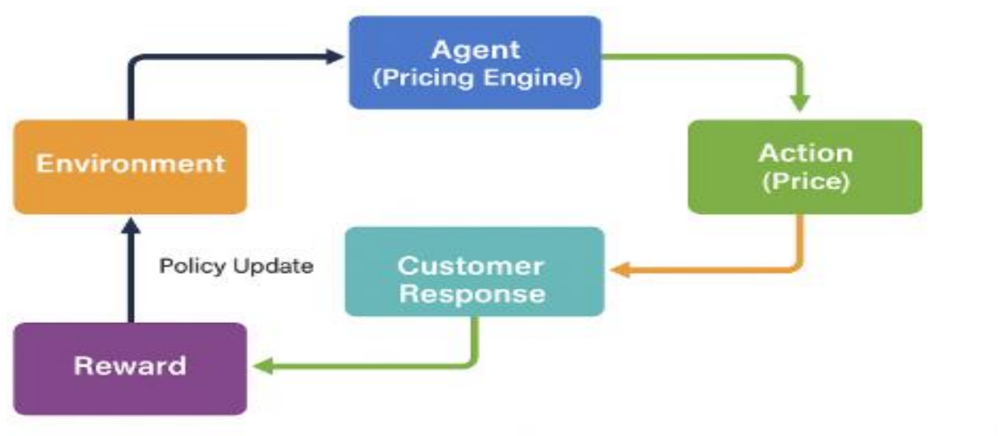

Figure 6.1: Reinforcement Learning Loop in Dynamic Pricing

An reinforcement learning agent explores and exploits this environment to maximize cumulative reward over time. By integrating algorithms like **Q-Learning**, **Deep Q Networks (DQN)**, or **Actor-Critic Methods**, these systems continuously improve pricing decisions using real-time feedback, allowing price adaptation even under **non-stationary market dynamics (Priyadarshini and Pandian 2024)**

ISBN: 978-81-988536-2-2

The Need for Dynamic Pricing

In a digital-first economy characterized by rapidly fluctuating supply-demand cycles, static pricing mechanisms are increasingly inadequate. E-commerce platforms often deal with hundreds of thousands of SKUs, each influenced by variables such as competitor pricing, time of day, customer loyalty, inventory levels, and user preferences. Embedding dynamic pricing capabilities within conversational commerce interfaces allows for real-time responsiveness to market stimuli (Kumari, 2024)

6.2. Reinforcement Learning Framework

Reinforcement learning offers a computational framework in which agents learn optimal pricing policies through trial-and-error interactions with the environment. In the context of retail, the agent is the pricing engine, the environment includes user responses and market conditions, and the reward signal reflects KPIs such as revenue, margin, or click-through rate (Fu et al., 2024).

Components of Reinforcement learning in Pricing:

- **State Space**: Customer profile, browsing history, stock levels, session context
- **Action Space**: Discrete or continuous price points
- **Reward Function**: A composite metric combining conversion, profit, and engagement

ISBN: 978-81-988536-2-2

- **Policy**: A function determining the best price for a given state

The Reinforcement learning model updates its policy using feedback signals (e.g., purchase, bounce, cart abandonments), thus refining its pricing decisions over time. Algorithms like Q-learning, Deep Q Networks (DQN), and Proximal Policy Optimization (PPO) are commonly used in commercial implementations.

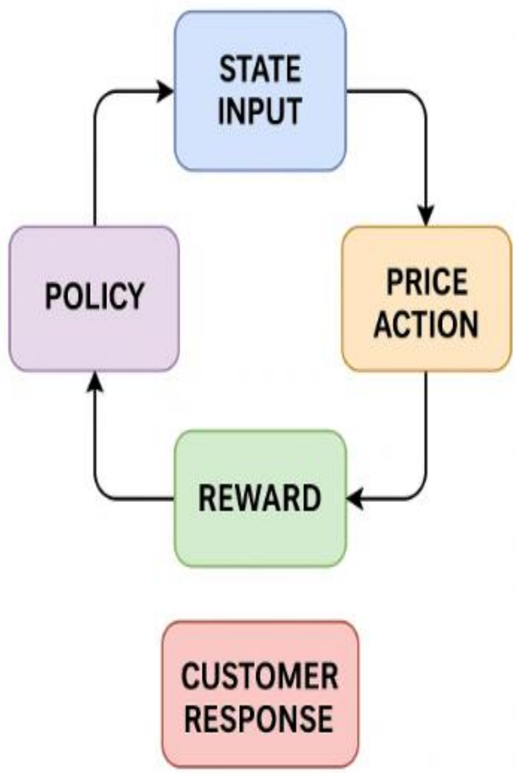

Figure 6.2: Real- Time Pricing Using Reinforcement Learning

a) AI-Based A/B Testing for Offers and Promotions

While A/B testing remains a foundational tool in evaluating promotional strategies, its conventional static form is inefficient in fast-evolving digital

ISBN: 978-81-988536-2-2

ecosystems. AI-powered experimentation frameworks accelerate discovery, reduce regret, and personalize promotional messages in real time. Traditional A/B testing allocates fixed traffic proportions to test variants and evaluates their success based on aggregated metrics over time. This approach is time-consuming, statistically inefficient, and lacks personalization. In highly competitive environments, the **opportunity cost of showing suboptimal promotions to a large segment** can be significant (Soundarapandian, 2024)

Modern AI-based experimentation replaces static traffic allocation with **adaptive algorithms** such as:

- **Multi-Armed Bandits (MABs)**: These dynamically adjust the traffic to promotional variants based on real-time performance.
- **Bayesian Optimization**: Learns probabilistic distributions of promotion performance and samples based on posterior uncertainty.
- **Contextual Bandits**: Incorporate user-specific features (e.g., age, device type, browsing intent) to tailor promotional exposure (Pancini,2024).

These algorithms balance exploration (testing new options) with exploitation (using high-performing strategies)—a trade-off that enhances decision-making over time.

Table 6.1: Comparison of Testing Strategies

Feature	**Classical A/B Testing**	**AI-Based Bandits**
Traffic Allocation	Fixed	Adaptive

ISBN: 978-81-988536-2-2

Learning Efficiency	Low	High
Personalization	Not Supported	Supported
Time to Optimization	Slow	Fast

b) Multi-Armed Bandits and Bayesian Optimization

Unlike static traffic allocation, multi-armed bandit (MAB) models assign a larger share of traffic to promising promotional variants while still exploring alternatives. Bayesian approaches further refine this by estimating the posterior distribution of expected performance, allowing uncertainty-aware exploration.

Key components include:

- Thompson Sampling for probabilistic selection
- Bayesian UCB (Upper Confidence Bound) for risk-sensitive learning
- Contextual Bandits to personalize based on user or session data

Table 6.2: A/B Testing vs. AI-Based Promotional Testing

Criteria	**Traditional A/B Testing**	**AI-Based Experimental Design**
Traffic Allocation	Fixed	Adaptive and Real-Time
Speed of Learning	Slow	Rapid
Optimization Objec	Binary Comparison	Continuous Reward Maximization
Personalization	Not Supported	Contextual (Segmented)

ISBN: 978-81-988536-2-2

Practical Advantages

- Reduced time to optimal offer identification
- Lower revenue loss during suboptimal testing
- Scalability across multiple audience segments and product categories

Platforms like Amazon and Netflix are already leveraging bandit-based frameworks to dynamically test visuals, discounts, and message wording in real time—far surpassing the yield of classical experimentation.

Behavioral Economics Fused with Predictive Analytics

While machine learning predicts what users are likely to do, **behavioral economics explains why**. Human behavior is often non-rational, driven by cognitive biases and heuristics such as:

- **Anchoring**: Reference prices influence perceived value.
- **Loss Aversion**: People prefer avoiding loss over acquiring gains.
- **Scarcity Bias**: Limited-time or low-stock messages increase urgency.
- **Framing Effect**: The way offers are presented affects decisions.

AI models that incorporate these psychological cues within their training frameworks achieve **greater behavioral resonance** and engagement.

ISBN: 978-81-988536-2-2

The final axis of intelligent promotion involves blending behavioral economics insights with machine-learned predictive models. Whereas machine learning focuses on patterns, behavioral economics illuminates why customers behave the way they do—even when their actions are irrational by classical standards.

6.3. Behavior-Driven Predictive Features

In practical applications, promotion engines derive behavioral features such as:

- Propensity to convert based on urgency
- Historical response to different reward types (discount vs. cashback)
- Likelihood to share a promotion socially
- Tendency to abandon carts after viewing reviews

These features are then fed into machine learning models like Gradient Boosted Trees, Neural Networks, or Transformers for offer recommendation or personalization (Cabrera,2024).

ISBN: 978-81-988536-2-2

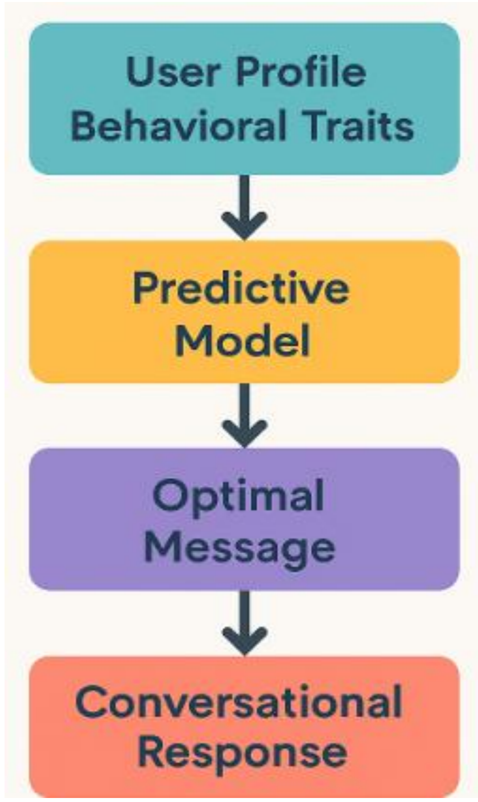

Figure 6.2: Behavioural -AI Promotion Framework

6.4. Psychological Triggers as Features

Predictive pipelines now incorporate variables inspired by choice architecture, such as (Gary, 2025)

- Anchoring effects: Influencing purchase decisions by showing high-priced items first
- Scarcity cues: Displaying limited inventory or countdown timers
- Framing: Presenting discounts as gains (“Save ₹500!”) vs. losses (“Lose ₹500 if you wait”)

ISBN: 978-81-988536-2-2

These behavioral elements are encoded into feature vectors that are fed into classifiers or regressors predicting:

- Conversion probability
- Bounce likelihood
- Abandonment thresholds

6.5. Dynamic Personalization

Behavioral insights are not monolithic. Different user segments respond differently to the same psychological cue:

- Price-conscious users react strongly to percentage-off offers
- Brand-loyal users respond to exclusivity or early-access language
- Impulse shoppers are more influenced by urgency and scarcity

The integration of reinforcement learning, intelligent experimentation, and behavioral economics into pricing and promotion strategies marks a new era in conversational commerce. Rather than setting prices or offers manually, systems now learn optimal strategies dynamically, adapting in real-time to user behavior, market trends, and psychological context (Ebadi Jalal and Elmaghraby, 2024)

This triadic fusion of algorithmic learning, real-world economics, and human cognition enables:

ISBN: 978-81-988536-2-2

- Agile and responsive pricing engines
- Promotion systems that optimize continuously
- Deep personalization rooted in behavioral nuance

By moving beyond static segmentation and periodic analysis, intelligent pricing and promotion frameworks can create adaptive, empathetic, and profitable customer interactions that define the future of AI-driven retail.

ISBN: 978-81-988536-2-2

References

1. Shan, Wenli. "Optimal pricing strategies and decision-making systems in e-commerce using integrated fuzzy multi-criteria method." *Expert Systems* 42.1 (2025): e13468..
2. Jain, R., & Kumar, A. (2024). Artificial intelligence in marketing: Two decades review. *NMIMS Management Review*, *32*(2), 75-83.
3. Powell, K. M., Machalek, D., & Quah, T. (2020). Real-time optimization using reinforcement learning. *Computers & Chemical Engineering*, *143*, 107077.
4. Kumari, A. (2024, March). Dynamic pricing: Trends, challenges and new frontiers. In *2024 IEEE international conference on contemporary computing and communications (InC4)* (Vol. 1, pp. 1-7). IEEE.
5. Priyadarshini, A., & Pandian, D. (2024, October). Sustainable Energy Efficient Unmanned Aerial Vehicles with Deep Q-Network and Deep Deterministic Policy Gradient. In *2024 International Symposium on Networks, Computers and Communications (ISNCC)* (pp. 1-6). IEEE.
6. Fu, B., Gao, Y., & Wang, W. (2024). A physics-informed deep reinforcement learning framework for autonomous steel frame structure design. *Computer-Aided Civil and Infrastructure Engineering*, *39*(20), 3125-3144.
7. Soundarapandian, R. (2024, September). Artificial intelligence (AI) Powered Strategies for optimizing A/B Testing. In *2024 Asian Conference on Intelligent Technologies (ACOIT)* (pp. 1-5). IEEE.
8. Pancini, M. (2024). Enhancing Data Preparation with Adaptive Learning: A Contextual Bandit Approach for Recommender Systems.

ISBN: 978-81-988536-2-2

9. Cabrera, Á. A. (2024). *Behavior-Driven AI Development* (Doctoral dissertation, UC Berkeley).
10. Gary, J. (2025). Information push strategies in e-commerce: emotional and cognitive mechanisms shaping purchase decisions: multi-method approaches. *Journal of Marketing Analytics*, 1-39.
11. Ebadi Jalal, M., & Elmaghraby, A. (2024). Analyzing the Dynamics of Customer Behavior: A New Perspective on Personalized Marketing through Counterfactual Analysis. *Journal of Theoretical and Applied Electronic Commerce Research*, *19*(3), 1660-1681.