Development Economics of China
2026, VOL. 10, NO. 1, 56-60
DOI: 10.47297/wspdecWSP2515-797312.20261001

Application of Human-Machine Collaborative Dynamic Pricing Systems in Chinese E-commerce Enterprises

Kainuo Zhu

City University of Macau, Macau, 999078, China

ABSTRACT
This paper examines the application of human-machine collaborative dynamic pricing systems in Chinese e-commerce enterprises. Moreover, in the context of China's highly transparent and fiercely competitive e-commerce market, traditional pricing methods could indicate that they have become inadequate in terms of the significant timeliness and critical precision, which may suggest that human-machine collaboration represents an emerging mainstream approach to pricing decisions. However, the article first analyzes market background and inevitability of this model's rise. Thus, it may delve into its three core technical components: machine learning prediction models, real-time market data monitoring, and human-machine interactive review and intervention mechanism. Nevertheless, from implementation perspective, it discusses core operational and management considerations for enterprises. Given that enterprises require technological foundation, the article might examine methods for strategic coordination and team and process development. Furthermore, this paper may provide e-commerce enterprises with framework for building efficient and robust intelligent pricing systems, spanning from theory to practice.

KEYWORDS
Human-machine collaboration; Dynamic pricing; E-commerce

1 Introduction

In China, the world's largest and most competitive e-commerce market, pricing could indicate that it has become a significant core factor that might substantially influence consumer decisions and the survival of businesses. However, the high transparency of information may suggest that the rapid responses of competitors affect the changing nature of consumer demands. Given that traditional static pricing strategies based on cost or experience appear increasingly inefficient, enterprises now face dual pressures of profit erosion and market share decline. Moreover, the "human-machine collaboration" dynamic pricing system might indicate integration of machine intelligence and human judgment. Thus, this system may achieve real-time price optimization amid vast data through algorithms. Furthermore, the system could ensure that pricing behaviors align with business goals through strategic human intervention. Nevertheless, this paper may examine the development status and key technological frameworks. In light of the essential management foundations, the successful implementation of this model in China's e-commerce sector could provide relevant enterprises with a roadmap for intelligent transformation of pricing.

2 Development Status of Dynamic Pricing Systems in China's E-commerce Sector

2.1 Competitive Environment and Pricing Demands in China's E-commerce Market

China's e-commerce market is one of the world's largest and most fiercely competitive digital business ecosystems. The landscape is characterized by a coexistence of high concentration and diversity, with leading platforms such as Alibaba, JD. com, and Pinduoduo dominating the majority of the market share. Meanwhile, numerous vertical e-commerce platforms, brand-owned official websites, and emerging live-streaming commerce players continue to enter the market, intensifying price competition to a cut-throat level. The significant information environment may indicate that consumers could readily examine prices across the important digital platforms and might demonstrate considerable sensitivity to these critical price fluctuations. Moreover, this condition appears to compel enterprises to shift pricing strategies from static models to dynamic approaches. Furthermore, enterprises may need to adopt agile market-responsive strategies. However, businesses might effectively attract customers while safeguarding profit margins. Nevertheless, enterprises could retain the price-sensitive customer base through dynamic pricing.

In such an environment, enterprises face exceptionally complex and multi-dimensional pricing demands that could indicate significant operational challenges. However, the pricing strategies may suggest that internal costs and profit objectives must be considered alongside real-time responses to competitors' pricing adjustments, fluctuations in supply chain costs, and changes in market supply-demand dynamics. Special strategies during major promotional events might affect these considerations. Furthermore, differentiated pricing for segmented markets and personalized offers based on user profiles have become critical for improving conversion rates. Given that speed, precision, and complexity are required, the combined requirements may exceed the capabilities of traditional manual decision-making. Thus, an urgent

need for implementation of data-driven dynamic pricing systems capable of processing vast amounts of information in real-time appears evident.

2.2 The Rise of Human-Machine Collaboration in Pricing Decision-Making

The early applications of purely algorithm-driven automated pricing systems could indicate that these significant computational approaches revealed important shortcomings, such that the critical technological implementations might potentially trigger destructive "price wars" due to data biases or model flaws. Moreover, the systems may exhibit inflexibility in response to sudden market events. These risks have prompted Chinese e-commerce enterprises to explore a robust "human-machine collaboration" model. Thus, the core of this model might lie in integrating computational power of machines with experiential judgment of humans. Nevertheless, machines may be tasked with processing vast amounts of data, monitoring market fluctuations, running predictive models, and generating pricing suggestions. However, human operators are responsible for setting strategic objectives, reviewing decisions, handling exceptional situations, and optimizing algorithmic rules.

The rise of this collaborative model could stem from the significant balancing advantages that the system may demonstrate. Moreover, the system might monitor the critical pricing data, the inventory levels, and the relevant demand signals across the entire network without interruption, potentially achieving that millisecond-level responsiveness that appears unattainable through human efforts alone. Furthermore, human experts may infuse important commercial intuition into the decision-making process. Given that brand value considerations and long-term customer relationships require human judgment, experts could provide that compliance requirements prevent short-sighted pricing decisions. However, strategic pricing for new product launches might require human judgment. Thus, human-machine collaboration may form a synergistic loop characterized by machine execution and human governance, establishing the mainstream approach for enterprises to achieve intelligent pricing today.

2.3 Challenges and Transformation of Traditional Pricing Methods

The traditional pricing methods, such as the cost-plus method, competitive benchmarking, or static promotional pricing, could indicate that these approaches demonstrate significant challenges in the contemporary fast-paced e-commerce environment. Moreover, the primary issues may suggest lagging nature and lack of precision. However, price adjustment cycles might be too long to keep up with competitors' price changes that occur hourly or by the minute. Given that pricing decisions are often based on historical data or limited samples, they may lack perception of real-time market conditions. Furthermore, it appears difficult to achieve refined and differentiated management for vast numbers of SKUs. During promotional periods, manually setting and modifying prices might be highly prone to errors and fails to maximize revenue. Nevertheless, these limitations could directly lead to missed sales opportunities, profit loss, or passive positioning in price wars.

To address these challenges, a profound pricing transformation may be underway. Moreover, the core of this significant transformation could indicate that enterprises are shifting from "experience-driven" fixed pricing models to "data-driven" dynamic pricing approaches. Enterprises might begin to build data platforms that integrate internal and external data sources. Given that these platforms provide the foundation, enterprises deploy pricing algorithm models based on these integrated systems. This transformation may not only involve upgrading technological tools but could also encompass reshaping organizational processes. Furthermore, pricing authority appears to be partially transferred from marketing or finance departments to specialized teams composed of data analysts, algorithm engineers, and operations personnel. Nevertheless, the decision-making process might evolve from "regular meeting reviews" to a combination of "real-time system suggestions and manual review confirmation." Thus, this transformation could turn pricing from a back-end management function into a front-line core competitive weapon. However, enterprises may also establish pricing as a profit engine through human-machine collaboration.

3 Core Technical Components of the Human-Machine Collaborative Dynamic Pricing System

3.1 Machine Learning Algorithms and Price Prediction Models

Machine learning algorithms could serve as the intelligent core of dynamic pricing systems, functioning to construct the accurate demand models and the significant price-response prediction models. Moreover, systems may typically employ algorithms such as ensemble learning methods, regression models, or deep learning approaches. However, analyzing vast amounts of historical sales data shows these algorithms uncover complex relationships. In light of the extensive user behavior data and external market data available, algorithms might reveal important relationships among multiple variables. Additionally, the relevant variables include price levels, promotional activities, seasonality patterns,

and competitive dynamics, thereby predicting expected sales volume and profit for specific products at different price points. Notwithstanding the complexity of forecasting challenges, gradient boosting tree models could be used for sales forecasting tasks. Furthermore, neural networks may help assess personalized price sensitivity among users effectively. Nevertheless, these models appear to provide a scientific foundation and quantitative foundation for identifying optimal pricing points.

The system relies on a closed-loop iterative optimization mechanism that could indicate this approach may ensure the continued effectiveness of these significant machine learning models. Moreover, models might collect real-time market feedback data through methods like A/B testing after deployment. Furthermore, the data appears to provide incremental learning updates. However, methods may address challenges like data drift. Thus, cold starts could present difficulties. Given that prediction accuracy remains critical, the system must be equipped with a robust monitoring framework that might continuously track prediction errors and important business metrics. In light of these operational requirements, the framework could ensure the stability of algorithmic decisions. Notwithstanding implementation complexities, accuracy may remain paramount. However, this ongoing self-optimization process may enable machine learning models to adapt to rapidly changing market environments. Therefore, the process could provide a reliable foundation for human-machine collaboration.

3.2 Real-Time Market Data and Competitor Monitoring

The comprehensive and precise real-time data monitoring could indicate that it serves as the critical "nerve endings" of these dynamic pricing systems, enabling the systems to perceive significant market changes. However, the primary task may suggest that it should achieve the high-frequency, large-scale external data collection, given that the core objective appears to demonstrate that tracking competitors' prices, inventory, and the promotional activities remains essential. Moreover, enterprises might typically deploy distributed web crawler clusters to collect target product information from e-commerce platforms, price comparison websites, and additional sources at minute-level frequency. Nevertheless, data may be integrated with internal sales, inventory, and cost information to build unified real-time data stream.

The system must process raw data through stream computing technologies for immediate feature extraction beyond data collection. Moreover, these significant technological capabilities could indicate that the system demonstrates the capacity to examine price differentials and rankings relative to competitors in real time, identify important promotional labels, and analyze relevant trends in category price indices. This real-time processing capability may enable the system to detect market fluctuations instantaneously. Notwithstanding these technical features, sudden price reductions by competitors or stockouts of popular products might trigger immediate responses from the pricing model. Thus, detection and conversion of market signals may provide the foundation for ensuring timeliness and proactivity of pricing strategy.

3.3 Human Review Rules and Decision Intervention Mechanisms

Human review rules and intervention mechanisms may serve as the "control valve" and "safety net" to demonstrate that the machine decisions could align with the business strategies. Moreover, the core implementation might rely on a rule engine, which could allow operational staff to constrain or adjust algorithmic recommendations by embedding predefined business logic. Furthermore, rules typically include price ceilings and floors, limits on price adjustment ranges, strategies targeting specific competitors, and clearance rules based on inventory status. Given that these mechanisms confine pricing behavior, the strategic boundaries and risk tolerance thresholds appear established. Nevertheless, intervention processes may show operational staff can adjust recommendations within defined parameters.

The system may provide flexible channels for manual intervention that could supplement the preset rules. Moreover, when encountering situations such as low model confidence, triggering of rule limits, or unexpected market events, the system might automatically initiate a manual review process, pushing the significant recommendations and the relevant justifications to operational personnel. Furthermore, operators exercise final decision authority to confirm, modify, or reject proposals. However, interventions are logged and fed back into the system to refine models and rules. Thus, this mechanism may grant human managers authority over critical decisions and exception handling but also facilitates collaborative evolution and strategic calibration through continuous feedback from interaction.

4 Core Considerations for System Implementation and Operational Management

4.1 Corporate Technological Foundation and System Deployment Path

The successful implementation of the system primarily depends on the enterprise's existing technological foundation and a pragmatic deployment approach. However, enterprises must first examine and solidify the core foundational capabilities, which may include a unified and clean data platform for products and transactions, compliant technical

means to stably acquire external data, and cloud computing resources that could support real-time computation. Moreover, without the significant high-quality data foundation, any advanced algorithms might prove ineffective. In terms of deployment strategy, an aggressive full-scale replacement could carry high risks; therefore, most enterprises tend to adopt a gradual approach. Nevertheless, pilot projects may begin with a single product category, specific promotional scenarios, or limited competitor benchmarking, utilizing relatively mature models and rules for small-scale validation. Given that enterprises seek validation at lower cost, this "gradual and iterative" approach allows verification of technical feasibility and business benefits while accumulating operational experience.

Following a successful pilot, the expansion of the system could reasonably indicate that enterprises establish a strong focus on the deep integration with these existing Enterprise Resource Planning (ERP), Supply Chain Management (SCM), and Customer Relationship Management (CRM) systems to achieve the automatic synchronization of critical data such as costs, inventory, and significant customer value. Moreover, the deployment process may suggest that enterprises incorporate a rigorous monitoring framework that tracks price changes and sales increases. Nevertheless, the process might indicate that enterprises monitor core metrics such as gross margin, brand index, and customer satisfaction. Technological deployment may show that implementation is an operational process requiring iteration and optimization. Given that systems require stable evolution, enterprises establish technical teams and maintenance procedures to ensure business support capabilities.

4.2 Coordinated Alignment of Pricing Strategies and Business Objectives

The effectiveness of a dynamic pricing system could ultimately demonstrate that its precise alignment with business strategy may necessitate dynamic coordination between pricing strategies and commercial goals. Moreover, during the system initialization, the important operations team might indicate that different pricing strategy model parameters and significant optimization objectives require configuration based on enterprise phased goals. Furthermore, when the market share growth appears as priority, the system can show more proactive competitive benchmarking rules seem necessary. However, when profit emphasis may appear relevant, price floors might require tightening with consideration given to customer willingness to pay. Thus, business side could translate macro-level strategies into quantifiable indicators and constraints that algorithms understand and execute.

Once the system might be operational, the coordinated adjustment could demonstrate that it manifests as the significant ongoing mechanism of calibration and feedback. Moreover, management teams may regularly examine the effectiveness of system pricing to analyze whether the pricing deviates from strategic intent. Given that the system frequently makes minor reductions to pursue conversions, it might harm profit margins and brand image, necessitating manual adjustments to weights or modifications. Additionally, the system should provide a dashboard, allowing managers to preview the impact of adjustments. However, this process of strategy setting, machine execution, and outcome evaluation may ensure that automation serves commercial intent. Nevertheless, the automation could adapt to changing intent rather than pursuing a solution.

4.3 Capacity Building of Operational Teams and Optimization of Collaborative Processes

The effectiveness of collaborative systems may depend on team capabilities and the design of these critical workflows. Moreover, the significant team development could indicate that organizations must substantially break through the traditional functional silos by establishing cross-functional groups that might integrate commercial operations, data analysis, and the relevant algorithmic technology. However, operational personnel appear to be no longer merely decision-makers for pricing activities. Thus, personnel may need to evolve into strategists and system supervisors. Given that business environments change, personnel might require the ability to interpret data while retaining business acumen to make judgments in exceptional scenarios. Enterprises must enhance team skills in data analysis and operating interfaces through systematic training.

At the process level, the clear and standardized collaboration protocols could indicate that these critical operational boundaries must be established between machine-automated decisions and manual reviews. Moreover, the important response procedures may suggest specific timelines for different alert levels. Furthermore, regular strategy meetings might demonstrate relevant review mechanisms. However, key processes may show phased deployment approaches. Thus, new rules could follow simulation testing approaches. Additionally, small-scale experimentation might indicate full deployment readiness. Given that daily operations require efficiency, the optimized workflow may suggest automated processes retain necessary human control at critical points. In light of these significant findings, human experiential wisdom might demonstrate that machine computational efficiency could be maximized through institutionalized means. Notwithstanding these observations, the human-machine collaborative system appears to enable sustainable operations.

5 Conclusion

The human-machine collaborative dynamic pricing system may represent a critical tool for Chinese e-commerce enterprises to enhance competitiveness and profitability in a complex market environment. Moreover, the success of this system could indicate that advanced machine learning algorithms and big data technologies provide important foundations. Furthermore, building a synergistic framework might demonstrate that the significant computational efficiency of machines requires deep integration with the strategic wisdom of humans. Given that enterprises must strengthen data and technological foundations, this approach may suggest adopting incremental deployment remains essential. In light of the evidence, close alignment between pricing strategies and dynamic business objectives could indicate that cross-functional operational teams provide key support. Nevertheless, optimizing collaborative workflows may show these factors affect implementation. However, the advancement of artificial intelligence technologies might indicate future expansion occurs. Thus, the exponential growth of market data could demonstrate boundaries of collaboration expand. Additionally, the depth of human-machine collaboration may suggest this integration continues. Notwithstanding these developments, the core principle could indicate that human-led decision-making empowered by machines remains unchanged. Therefore, this transformation may demonstrate that the significant pricing management in e-commerce enterprises evolves from operational tasks into precise strategic science. Furthermore, this evolution might indicate that these critical competitive advantages emerge as key outcomes.

References

[1] Zhang Yubo. Anti-Monopoly Compliance Regulation of Price Discrimination on E-commerce Platforms[J]. China Price Regulation and Anti-Monopoly, 2026, (01): 40-42.

[2] Cao Rui. Research on AI-Based Pricing and Demand Forecasting Models for E-commerce Products[J]. Computer Knowledge and Technology, 2025, 21(34): 12-14.

[3] Li Yongfeng. Analysis of the Impact of Big Data-Driven Dynamic Pricing Strategies on Consumers' Perception of Fairness[J]. Sales and Marketing, 2025, (20): 37-39.

[4] Yu Shuotong. Research on Pricing Decisions and Channel Choices in AI-Driven Live E-commerce Agricultural Product Supply Chains[J]. Business 2.0, 2025, (14): 13-15.

[5] Huang Jiali. A Review of Dynamic Pricing in Operations Management[J]. Cooperative Economy and Technology, 2025, (10): 75-77.

[6] Bhagat R., Chauhan V., & Bhagat P. Investigating the impact of artificial intelligence on consumer's purchase intention in e-retailing[J]. Foresight: the Journal of Futures Studies, Strategic Thinking and Policy, 2023, (02): 249-263.

[7] Bocean C., Popescu L., Simion D., Sperdea N., Puiu C., Marinescu R., & Maria E. The Role of AI Technologies in E-Commerce Development: A European Comparative Study[J]. Journal of Theoretical and Applied Electronic Commerce Research, 2025, (03): Article 225.

[8] Chenavaz R., & Dimitrov S. Artificial intelligence and dynamic pricing: a systematic literature review[J]. Journal of Applied Economics, 2025, (01): Article 2466140.

[9] Dumiter F. C., & Schebesch K. B. Using Artificial Intelligence to Determine the Impact of E-Commerce on the Digital Economy[J]. Journal of Theoretical and Applied Electronic Commerce Research, 2025, (03): Article 219.

[10] Hussain A., Ehsan M., & Rauf A. AI adoption and ethical capitalistic orientation: investigating the moderating effect of human–AI synergy in China SMEs[J]. International Journal of Ethics and Systems, 2025: 1-23.