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Supply Chain Coordination Models for Fresh Food E-Commerce Under AI Services

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Abstract

This study develops centralized and decentralized decision-making models for fresh food e-commerce supply chains, incorporating perishability characteristics and AI implementation costs. Optimization modeling was employed to examine the interactive mechanism between AI service levels and inventory strategies. Results showed that AI services significantly enhanced supply chain performance by reducing demand forecasting errors and operational costs, with optimal service levels achieved when marginal revenue equaled marginal costs. Decentralized decision-making exhibited pronounced dual marginal effects and AI investment externalities, leading platforms to overinvest in AI while reducing inventory levels. Additionally, the AI cost coefficient demonstrated nonlinear impacts on decision-making patterns, with higher technical costs exacerbating efficiency losses in decentralized models. These findings reveal the interactive mechanism between AI service levels and inventory strategies, providing theoretical foundations for AI investment decisions and supply chain coordination.

Keywords

Fresh e-commerce supply chain; Artificial intelligence services; Supply chain coordination; Stackelberg game.

1. Introduction

The rise of artificial intelligence technology in recent years has provided innovative solutions to address challenges in fresh food e-commerce supply chains. By leveraging machine learning algorithms to analyze multidimensional data—including historical sales records, weather patterns, holiday schedules, and social media sentiment—AI services enable precise demand forecasting, dynamic pricing optimization, intelligent inventory management, and optimized cold chain routing. However, the adoption of AI also introduces new decision-making complexities: How should AI implementation costs be allocated? How can AI capabilities be effectively integrated with inventory decision-making processes? And how do decentralized decision-making patterns between platforms and suppliers impact overall operational efficiency?

The application of AI technology in supply chains has yielded substantial research findings. In demand forecasting and inventory optimization, scholars have demonstrated that AI algorithms can effectively reduce prediction errors and mitigate bullwhip effects. Regarding supply chain structures, fresh food e-commerce platforms typically operate within a two-tier Stackelberg game framework consisting of retailers (platforms) and suppliers. Platforms are responsible for market demand forecasting and inventory decisions targeting end consumers, while suppliers dominate product supply and cold chain logistics services. However, existing research still exhibits notable limitations in the following aspects: First, the investment decision-making mechanism for AI services remains unclear. Although AI investments can reduce inventory costs and stockout losses, their cost functions exhibit significant marginal increasing characteristics. Current literature predominantly assumes exogenous AI deployment levels or independent decision-making, lacking theoretical frameworks for joint optimization of AI investment costs and inventory order quantities. Second, distortions in AI investments under decentralized decision-making are overlooked. When platforms and suppliers make independent decisions, suppliers as Stackelberg leaders profit from wholesale pricing, while platforms as followers—unburdened by suppliers' AI usage costs—may engage in distorted behaviors such as "over-investing in AI (to improve prediction accuracy) while reducing inventory." This novel dual marginal effect caused by AI externalities remains underexplored. Third, the interactive influence mechanism between perishable freshness of fresh products and AI services requires further elucidation. High loss rates demand greater prediction accuracy, yet simultaneously increase inventory holding costs and corruption risks. Existing literature predominantly focuses on physical preservation technologies (such as cold chain temperature control), overlooking the dynamic trade-off between AI prediction accuracy and product perishability characteristics. In summary, optimizing decentralized decision-making mechanisms between platforms and suppliers under dual constraints of escalating AI service marginal costs and perishable product attributes has become a critical scientific challenge in current fresh food e-commerce supply chain management.

While existing literature primarily focuses on inventory coordination issues in traditional supply chains, it rarely considers the joint optimization of AI service investments and inventory decision-making. This study integrates AI service costs into supply chain decision models, introduces product loss rate parameters tailored for fresh food e-commerce scenarios, and enriches the theoretical framework for perishable goods supply chain management. It elucidates the impact mechanism of AI investment externalities on supply chain efficiency, expanding the research boundaries of supply chain coordination theory. The findings provide decision-making support for AI investment strategies of fresh food e-commerce platforms and suppliers. Through quantitative analysis of efficiency differences between centralized and decentralized decision-making, the study highlights the necessity and potential benefits of supply chain coordination, offering theoretical foundations for designing coordination contracts such as revenue sharing and cost-sharing mechanisms. Additionally, sensitivity analysis of AI cost coefficients helps enterprises adjust investment strategies according to technological development stages.

2. Literature Review

2.1. Research on Fresh E-commerce Supply Chain Management

Fresh e-commerce supply chain management has become a research hotspot in the field of operation management in recent years.

In recent years, the optimization and coordination of fresh food e-commerce supply chains have become a focal point in academic research. Studies primarily focus on four core dimensions: supply chain model innovation, coordination mechanism design, logistics technology empowerment, and quality safety management. Regarding supply chain models and strategic choices, Wang Tian (2026) noted that while the forward warehouse model achieves the "30-minute delivery" efficiency advantage, it faces supply chain bottlenecks such as high costs, customer acquisition challenges, and market penetration barriers. Pupu Supermarket has provided an industry differentiation path by achieving break-even through deep user base cultivation. Wu Xiaozhen (2025) developed a three-dimensional supply chain strategy framework of "data-driven decision-making, partner collaboration, and green response" from a dynamic capability perspective. Using analytic hierarchy process (AHP) analysis, she demonstrated that ecosystem partnership strategies significantly outperform predictive procurement and direct procurement systems. The study recommends advancing supply chain upgrades through forward warehouse sharing, flexible transportation capacity pooling, and industry-level data open platforms.

2.2. Research on Supply Chain Coordination and Contract Design

To address supply chain coordination and information asymmetry challenges, scholars have employed game theory and contract design methodologies for in-depth research. Liang (2026) developed a supply chain model incorporating stochastic demand and freshness dependence, demonstrating that voluntary information sharing under agency models enables win-win outcomes for suppliers and platforms. In resale and hybrid models, information sharing still enhances overall profitability when suppliers maintain sufficiently high freshness preservation efficiency. Zhang Shuxian (2025) analyzed AI technology's impact on supply chain information sharing value, noting that while AI doesn't alter information-sharing strategies, both parties' value increases synchronously with AI technological advancement in consignment models, whereas resale models exhibit value fluctuations dependent on freshness elasticity. Qin Zhidan (2025) validated through Stackelberg game theory that moderate price competition outperforms non-competitive models, significantly boosting freshness preservation efforts, market demand, and supply chain profits under competitive conditions. Li Jinya (2025) constructed a three-tier supply chain game model involving suppliers, third-party logistics providers, and e-commerce platforms, warning that excessive order placement by e-commerce entities may expose them to full forecasting risks and losses, recommending conservative demand forecasting strategies. Shao (2026) addressed information asymmetry issues in third-party logistics through cost-sharing-profit-sharing contracts for inflated freshness preservation efforts, proving such contracts enhance preservation standards while achieving profit growth across supply chain members. In the realm of supply chain logistics and technological empowerment, Du Junwei (2025) identified four optimization strategies leveraging digital technologies to address supply chain pain points including cold chain disruptions, inefficient information coordination, and inadequate quality control traceability. He emphasized achieving intelligent supply chain transformation through blockchain-based traceability and data sharing. Han Xingzhu (2025) highlighted that lagging cold chain logistics has become a critical bottleneck constraining fresh food e-commerce supply chain development, calling for systematic improvement strategies for existing models. Song Yikang (2025) systematically reviewed the current research status of last-mile delivery, noting that "last mile" delivery costs and efficiency remain core challenges in supply chain optimization.

Literature review reveals that existing research on fresh food e-commerce supply chains primarily focuses on traditional factors such as preservation and cold chain logistics, lacking theoretical models for AI-driven service decision-making. Studies on AI investment decisions often operate independently from inventory management strategies, failing to account for their interactive effects. Research addressing AI service externalities and supply chain coordination mechanisms remains insufficient. Addressing these gaps, this study develops a supply chain decision-making model incorporating AI services, with key analyses including: joint optimization of AI service levels and inventory order quantities; efficiency differences between centralized and decentralized decision-making approaches along with dual marginal effects; and nonlinear impacts of AI cost coefficients on supply chain decisions. Numerical simulations validate theoretical conclusions, providing managerial insights for AI investment strategies and coordination mechanism design in fresh food e-commerce supply chains.

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3. Model

3.1. Problem Description and Technical Assumptions

This section investigates centralized and decentralized decision-making models for the Fresh E-commerce Supply Chain (FESC) based on AI services. By integrating AI solutions, FESC achieves cost reduction and efficiency enhancement through optimized fresh produce loss control and improved demand forecasting accuracy. Fresh e-commerce platforms utilize AI-driven market demand prediction (via market analysis→AI data collection→feature engineering→algorithm modeling→intelligent forecasting→real-time monitoring) to place orders with suppliers. Suppliers then coordinate harvesting, pre-cooling, packaging, and cold chain logistics according to platform orders. The technical framework is based on the following assumptions:

Technical Hypothesis (1): FESC constitutes a two-tier supply chain comprising fresh food e-commerce platforms and suppliers, both functioning as rational, risk-neutral economic entities. The dominant fresh food e-commerce platform, serving as the designer and provider of integrated solutions, imposes stringent requirements on its supplier partners. By leveraging technologies such as AI, IoT, and blockchain, the platform strategically coordinates the dispersed production capacities and cold chain resources of suppliers. Through AI-driven services, it virtualizes existing supplier capabilities and cold chain assets, dynamically adapting them to meet consumers' personalized and diverse needs.

Technical Hypothesis (2): Fresh food e-commerce platforms directly engage with end consumers, who submit demand information—including location, quantity, and freshness preferences—to the platform. However, the actual provision of product supply and cold chain logistics services is undertaken by fresh food suppliers.

Technical Hypothesis (3): With FESC's integration of AI services, information symmetry exists between fresh food e-commerce platforms and suppliers. Leveraging AI-driven information sharing capabilities, suppliers utilize AI algorithms and smart temperature control systems to monitor product quality throughout the supply chain, track c_d real-time inventory levels, freshness status, and logistics progress. Simultaneously, suppliers relay this data to e-commerce platforms and consumers. The cost of adopting AI services for suppliers is assumed to be c_d.

Technical Assumption (4):The supply capacity of fresh product suppliers is unlimited, thereby fully satisfying the ordering demands of the fresh e-commerce platform. The market demand under study is stochastic, where one unit of consumer demand requires one unit of product inventory to fulfill. Due to the perishability of fresh products, inventory decays at a rate of λ （$0<\lambda<1$） during the holding period. Consequently, the actual salable quantity is defined as $Ke^{-\lambda}$, where the freshness-keeping rate is $\beta=e^{-\lambda}$. Furthermore, market demand is influenced by the supply-demand relationship and AI services. The impact of AI services on market demand stems from improved prediction accuracy and reduced stockout rates, which indirectly drive changes in market demand.

Table 1.Symbolic meanings

symbol	meaning	symbol	meaning
x	Market demand	η	AI service cost coefficient
s	AI service level ($0\le s\le 1$)	λ	Fresh product loss rate
θ	AI cost optimization coefficient	c_d	Cost of AI services for suppliers

symbol	meaning	symbol	meaning
$f(x)$	market demand density function	$F(x)$	market demand distribution function
$S(K)$	Fresh product platform expected sales volume	p	Unit price of products sold on fresh food platforms
w	wholesale price of products	c_s	Supplier's unit production cost
π_r	Profit of Fresh Food E-commerce Platform	π_s	Supplier's profit
μ	average market demand	T	expected transfer payment
g	Unit shortage loss of fresh food platforms during inventory shortages	K	Product order volume on fresh food platforms
π_{sc}	The total profit of FESC	c_r	Unit operating cost of fresh food platforms
$L(K)$	Expected inventory shortage	h	Supplier's unit inventory holding cost (including cold chain)
v	Unit residual value of expired fresh products	β	Preservation rate ($\beta=e^{-\lambda}$)

3.2. Centralized Decision-Making Model

During centralized decision-making processes under AI services, fresh food e-commerce platforms and suppliers collaborate to maximize overall FESC benefits. As the integrator of FESC systems, these platforms leverage AI solutions to reduce operational costs and minimize product losses. Supplier costs include unit production expenses, while platform costs encompass operational expenditures, inventory holding costs, and AI implementation investments. Based on the technical assumptions and parameter settings outlined in the previous section, the profit margins for fresh food e-commerce platforms, suppliers, and FESC systems under AI-driven operations can be calculated as follows:

Profit of fresh E − commerce Platform: $\pi_r=pS(K)+vI(K)-wK-c_r(1-\theta s)K-hI(K)-gL(K)-\eta s^2$

Profit of fresh supplier： $\pi_s=(w-c_s)K-c_d s$

Total Profit of the FESC： $\pi_{sc}=\pi_r+\pi_s=pS(K)+vI(K)-c_r(1-\theta s)K-c_s K-hI(K)-\eta s^2-c_d s-gL(K)$

Here, $S(K)$ denotes the expected sales volume considering fresh product deterioration, $I(K)$ represents the expected remaining inventory, and $L(K)$ stands for the expected shortage quantity. For a uniform distribution $U(a,b)$, incorporating the freshness-keeping rate $\beta=e^{-\lambda}$, we have:

$$S(K)=\beta K-\frac{(\beta K-a)^2}{2(b-a)},\quad I(K)=\frac{(\beta K-a)^2}{2(b-a)},\quad L(K)=\frac{(b-\beta K)^2}{2(b-a)}$$

When making centralized decisions, with the goal of maximizing the overall profit of FESC, based on technical assumptions, by setting decision variables: product order quantity (K) and AI service level (s), the FESC centralized decision-making model can be obtained:

$$\max_{K,s} \pi_{sc} = pS(K)+vI(K)-c_r(1-\theta s)K-c_sK-\mathrm{h}I(K)-\eta s^2-c_ds-gL(K)$$

Since $\frac{\partial^2\pi_{sc}}{\partial K^2}=-(p-v+g+\mathrm{h})\frac{\beta^2}{b-a}<0$, $\frac{\partial^2\pi_{sc}}{\partial s^2}=-2\eta<0$ and $\frac{\partial^2\pi_{sc}}{\partial K\partial s}=c_r\theta\beta$, it follows from the properties of the Hessian matrix that when $\eta>\frac{(c_r\theta\beta)^2(b-a)}{2(p-v+g+\mathrm{h})\beta^2}$, the matrix is negative definite. Consequently, the FESC profit function under AI services is strictly concave with respect to K and s, ensuring a unique optimal solution. By setting $\frac{\partial\pi_{sc}}{\partial K}=0$,$\frac{\partial\pi_{sc}}{\partial s}=0$. the optimal order quantity $K*$and AI service level $s*$ satisfy the following conditions:

$$F(\beta K^)=\frac{(p+g)\beta-c_r(1-\theta s^)-c_s}{(p-v+g+\mathrm{h})\beta} \quad s^*=\frac{c_r\theta\beta K^*-c_d}{2\eta}$$

In the FESC under AI services, since AI services enhance operational efficiency and reduce deterioration, it is observed that the optimal AI service level$s^*$is a decreasing function of the AI service cost coefficient η. Furthermore, when $c_r\theta\beta K^*>c_d$, the optimal order quantity K^* is positively correlated withη. Specifically, an increase inηleads to a reduction in s^*, which in turn induces the platform to increase its order quantity to compensate for the efficiency loss.

3.3. Decentralized Decision-Making Model

In the decentralized decision-making scenario of the FESC under AI services, the fresh e-commerce platform and the fresh supplier make decisions independently, each aiming to maximize their own interests rather than the total FESC profit. At the beginning of the sales cycle: the fresh e-commerce platform orders products from the fresh supplier based on AI predictions, and the fresh supplier determines the wholesale price (w) based on the product order quantity (
K). The platform bears the inventory holding costs and AI investment costs, while the supplier bears the AI usage costs.

At this stage, the profit of the fresh e-commerce platform is given by:

$$\pi_r=pS(K)+vI(K)-wK-c_r(1-\theta s)K-\mathrm{h}I(K)-gL(K)-\eta s^2$$

Where $S(K)=\int_a^{\beta K} xf(x)dx+\beta K(1-F(\beta K))$, $L(K)=\frac{(b-\beta K)^2}{2(b-a)}$, $I(K)=\beta K-S(K)$

The profit of the fresh supplier is:: $\pi_s=(w-c_s)K-c_ds$

In the FESC, the fresh e-commerce platform predicts market demand based on AI services and determines the optimal order quantity (K) and AI service level (s) to maximize its own interests. Assuming that the price provided to consumers by the platform is the result of market gaming, and under the condition that the platform maximizes its own interests, taking the second-order partial derivative with respect to the order quantity (K) yields:

$$\frac{\partial^2\pi_r}{\partial K^2}=-(p-v+g+\mathrm{h})\frac{\beta^2}{b-a}<0$$

According to the properties derived from the Leibniz rule, the profit of the fresh e-commerce platform is a strictly concave function of the order quantity (K). Setting $\frac{\partial\pi_r}{\partial K}=0$, we obtain the optimal order quantity

$$F(\beta K_r\ )=\frac{(p+g)\beta-w-c_r(1-\theta s)}{(p-v+g+\mathrm{h})\beta}$$

In decentralized decision-making, the AI service level (s) is decided by the fresh e-commerce platform to maximize its own profit. Taking the second-order partial derivative with respect to

(s) yields $\frac{\partial^2 \pi_r}{\partial s^2}$=-2$\eta$<0. It follows that the platform profit is a strictly concave function of the AI service level (s). Setting $\frac{\partial \pi_r}{\partial s}$ =0, we obtain the optimal AI service level s_r^*:$s_r^* = \frac{c_r \theta \beta K_r}{2\eta}$

Under centralized decision-making,$s_{sc} = \frac{c_r \theta \beta K_{sc}^* - c_d}{2\eta}$,

Under decentralized decision-making:

$$K_r^* = \frac{1}{\beta} F^{-1}\left(\frac{(p+g)\beta - w - c_r(1-\theta s_r^*)}{(p-v+g+h)\beta}\right), \quad s_r^* = \frac{c_r \theta \beta K_r^*}{2\eta}$$

The supplier selects the optimal wholesale price w^* based on the platform's reaction functions to maximize π_s, yielding:

$$w^* = \frac{(p+g)\beta + c_s - c_r(1-\theta s)}{2\beta} + \frac{c_d c_r \theta}{4\eta}$$

Because in the FESC under AI services, the platform under decentralized decision-making does not take into account the supplier's AI usage cost, this leads to an excessively high AI service level ($sr^* > s_{sc}^*$) and insufficient order quantity ($K_r^* < K_{sc}^*$), failing to achieve FESC coordination. In real-world market environments, as rational economic agents, the fresh e-commerce platform and fresh supplier in the FESC face efficiency losses due to the double marginalization effect and AI investment externalities. Consequently, they often opt for decentralized decision-making to optimize their individual interests, making it difficult to achieve FESC coordination.

4. Numerical Simulation

This section conducts numerical simulations on the centralized decision-making model and decentralized decision-making model of FESC based on AI services, with the following parameters set： p=50， c_r=5， c_s=20， h=3， g=15， v=8， η=100， θ=0.8， c_d=20， λ=0.05,β≈0.9512， This paper assumes that the random demand x faced by FESC follows a uniform distribution U(50, 150)

As illustrated in Figure 1, the 3D surface of the supply chain profit under centralized decision-making with AI services exhibits strict concavity. The function graph forms a typical unimodal surface, reaching a global maximum of at (K^*,s^*)=(95.42,0.58).Observing the variation in surface slope, the profit changes moderately within the region where K∈[85,105] and s∈[0.5,0.7], indicating that the supply chain possesses a certain degree of fault tolerance near the optimal solution. Conversely, the surface declines sharply when K<60 or K>130 . This reflects that both the shortage loss caused by insufficient fresh inventory and the spoilage cost caused by inventory excess significantly erode profits, which aligns with the economic characteristics of fresh products characterized by high deterioration rates and high time-sensitivity.

As shown in Figure 2, the 3D surface of the fresh e-commerce platform's profit under decentralized decision-making differs significantly from that of the centralized scenario. Given a wholesale price of w=35.20, the platform's optimal decision point is (K^*,s^*)=(72.15,0.72). Compared to the centralized decision, the AI service level increases by 24.1%, while the order quantity decreases by 24.4%.This deviation stems from the combined effects of double marginalization and AI investment externalities: since the platform does not bear the supplier's AI usage cost and only considers its own AI investment cost ηs^2, it tends to over-invest in AI. Meanwhile, due to the wholesale price being higher than the supplier's unit cost the platform faces a higher marginal procurement cost, which leads to a reduction in order quantity, ultimately resulting in a loss of total supply chain profit.

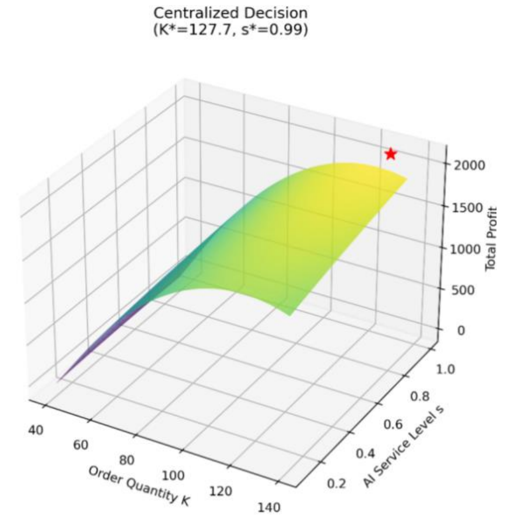

Fig. 1 3D profit surface under centralized decision

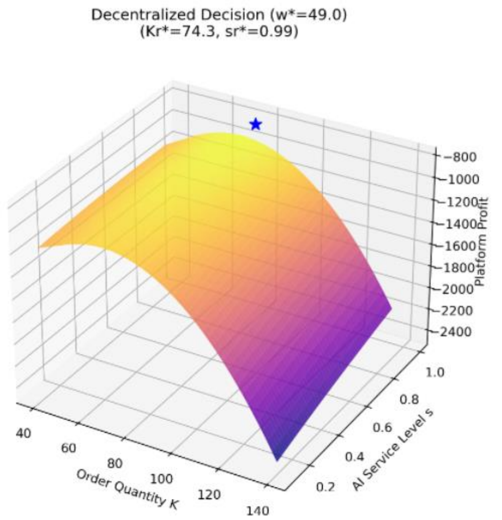

Fig. 2 3D profit surface of platform under decentralized decision

As illustrated in Figure 3, the impact of the AI service cost coefficient ηη on the optimal AI service level s exhibits non-linear characteristics. Whenη≤150, both s under centralized and decentralized decision-making remain at 1, indicating that when AI technology costs are low, all supply chain parties choose to maximize the AI service level. However, when η>150, the two curves begin to diverge; the decline rate of s_r * under decentralized decision-making is significantly faster than that of s^* under centralized decision-making. Specifically, at η=300, while s_r =0.47.This divergence stems from economies of scale: centralized decision-making maintains a larger order quantity through coordinated optimization, thereby spreading the unit AI cost; whereas, under decentralized decision-making, the platform's order quantity shrinks and cannot support high AI investment, causing it to exit the high AI level region more rapidly. This result suggests that the less mature the AI technology (i.e., the larger the η), the more severe the efficiency loss caused by decentralized decision-making, highlighting the greater need for coordination mechanisms to achieve supply chain optimization.

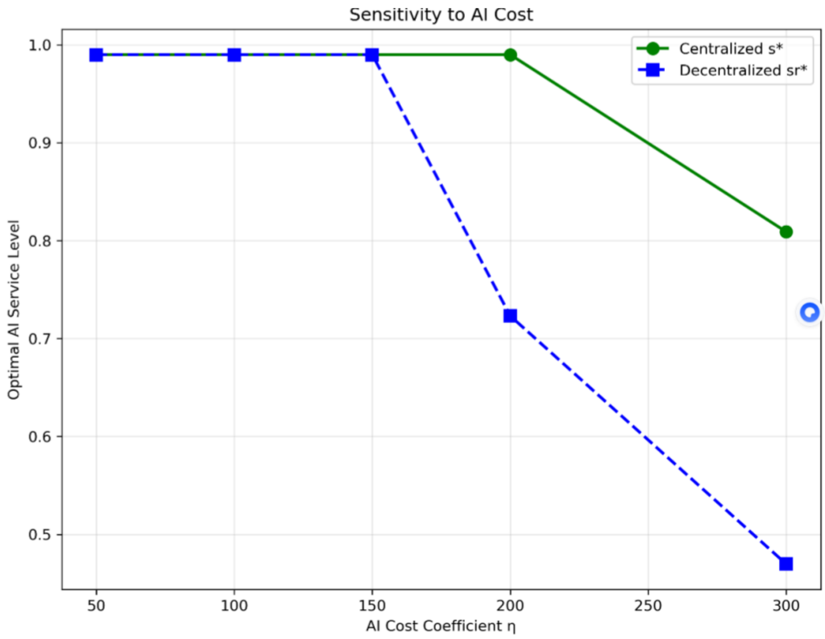

Fig. 3 Sensitivity analysis of AI cost coefficien

5. Conclusion

This paper investigates the centralized and decentralized decision-making models of a Fresh E-commerce Supply Chain (FESC) based on AI services. Through theoretical analysis and numerical simulation, the following main conclusions are drawn:(1)Marginal trade-off in optimal AI investment: AI services enhance supply chain performance by improving demand prediction accuracy and reducing inventory costs and shortage losses. However, due to the convexity of AI investment costs, there exists a unique optimal AI service level s^*. When the AI cost coefficient is low, the optimal AI level hits the boundary （$s^*=1$）.(2) Double marginalization and AI investment externalities in decentralized decision-making: Decentralized decision-making leads to a reduction in the platform's order quantity compared to centralized decision-making and results in over-investment in AI service levels. This causes overall supply chain efficiency loss and distorts AI investment decisions.(3) Non-linear impact of AI costs on decision modes: Sensitivity analysis shows that when the AI cost coefficient $\eta<150$, both centralized and decentralized decisions opt for the highest AI level ($s=1$), with insignificant differences. However, when$\eta>150$, the curves diverge, and the AI level in decentralized decision-making declines more rapidly. In high-cost environments, the shrinkage of order quantities in decentralized decision-making prevents the spreading of AI costs, trapping the supply chain in a vicious cycle of "low ordering - low AI" and exacerbating efficiency losses.(4) Product characteristics reinforce the necessity of coordination: High-deterioration fresh products require higher prediction accuracy. The superposition of shortage losses and spoilage costs caused by insufficient inventory under decentralized decision-making makes the coordination of the FESC more urgent than that of general supply chains.

Several limitations warrant further exploration. First, the assumptions of uniform demand and linear AI efficiency could be extended to more general distributions and non-linear functions. Second, the single-period Stackelberg model overlooks multi-period dynamics and long-term relationships. Finally, while the necessity of coordination is established, specific contract parameters for perfect coordination remain to be derived. Despite these constraints, this study provides a theoretical foundation for understanding AI mechanisms in the FESC and offers valuable insights for practice.

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