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AI technology sharing strategies for e-commerce platforms with private label introduction

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ABSTRACT

As the online retail market expands and brand competition intensifies, e-commerce platforms and retailers are facing increasing service and operational costs. The emergence of artificial intelligence (AI) technology has transformed the consumer shopping experience while simultaneously reducing retailers' operational costs. However, platforms must judiciously balance the operational efficiency improvements enabled by AI technology with the potential risks stemming from intensified competition and rising technology adoption costs. This study constructs a two-stage supply chain model involving a retailer and a platform, who are selling national brand products and substitutable private label brand, respectively. The platform strategically adopts and shares AI technology with retailer to optimise sales performance. We systematically analyze the viability of AI adoption and its impact on brand competition. The findings suggest that under moderate cost conditions, the platform's AI adoption may result in a lose-lose situation for both firms. When AI R&D costs are low, sharing AI technology, despite potentially weakening the platform's private-label competitiveness and reducing overall market demand, can still lead to a win-win situation for both parties. Additionally, extended analysis indicates that changes in consumer preferences have a limited effect on AI investment decisions, although different AI applications may introduce more complex supply chain dynamics.

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1. Introduction

The global e-commerce market is projected to exceed \$4.32 trillion by 2025 and is expected to grow at a compound annual growth rate of 8.02% over the next decade.¹ As the online retail market rapidly expands, leading e-commerce platforms are not only delivering essential online retail services but also sell private-label brands to enhance their profit. Recently, platforms like Amazon, JD.com, and REDnote have seen substantial growth in their private-label ventures (D. Li et al. 2021). However, with the continuous increase in market competition, e-commerce platforms and retailers face heightened brand rivalry while simultaneously experiencing sustained growth in operational cost pressures. To improve the consumer shopping experience, these enterprises are investing more in customer service, advertising, store design, and after-sales services. Data shows

that operational costs for retailers on Alibaba's platform can exceed 30% of their total revenue, while JD.com's self-operated model incurs costs as high as 80%.² These escalating expenses have become a significant bottleneck, hindering the profitability of e-commerce businesses. In 2019, at least 41 e-commerce platform companies in China went bankrupt due to excessive labour and operational costs.³ In this context, optimising operational processes and enhancing management efficiency to control costs effectively has become a critical challenge for e-commerce enterprises.

Recent advancements in AI-generated content have revolutionised e-commerce operations, enabling dynamic optimisation of recommendation systems and highly personalised user experiences. Leading platforms now deploy AI to automate marketing workflows. It supports targeted email campaigns and social media engagement,

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thereby reducing operational expenditures by up to 40% (Jauhar et al. 2024). Concurrently, both Amazon and SMZDM leverage their AI-powered assistants to achieve dual objectives: reducing operational expenditures while stimulating product demand. Sensory Fitness' virtual agent Sasha, is generating \$30,000 annual savings in customer support (Y. Wang et al. 2025). Current industry practices clearly demonstrate AI's transformative impact on e-commerce. Baidu Youxuan achieved 594% year-over-year gross merchandise volume growth in 2023, with AI-driven transactions accounting for 20% of total sales.⁴ Lenovo's AI-optimised e-commerce platform surpassed \$220 million in annual revenue, utilising machine learning for real-time demand forecasting. These innovations align with supply chain optimisations where AI reduces inventory waste through predictive analytics, as evidenced by Amazon's 15% logistics cost reduction. The AI-enabled e-commerce market is projected to reach \$16.8 billion by 2030, growing at a 15.7% compound annual growth rate.⁵

To establish a competitive advantage over branded products and enhance business profitability, many platforms are actively integrating AI technology into the operations of their private label products. For example, NetEase, China's largest internet portal, has leveraged AI-driven scenarios and Natural Language Processing (NLP) technologies to effectively promote several of its most popular games.⁶ In September 2023, NetEase launched 'Shanghe', an AI model specifically designed for customer service applications, aiming to enhance the private label's cost efficiency through an 'AIGC + customer service' approach.⁷ Meanwhile, Taobao, China's largest e-commerce platform, has showcased its leadership in AI adoption. Its private label brand 'Miaomifen' has fully deployed AI-powered customer service and an intelligent clothing size recommendation system. In contrast, many traditional brands on the platform have not yet achieved this technological breakthrough. In these cases, the platform exclusively provides AI technology for its own private label without sharing it with retailers.

In recent years, platforms have been expanding their business scope by selectively sharing AI technology with retailers selling their products through the platform. For instance, the e-commerce giant JD.com launched the 'AI Universal Service Package'. It uses AI tools to produce product images, videos, and live-streaming content. These services are provided to retailers free of charge. The company claims that this service can help merchants reduce operational costs by 50%.⁸ In 2025, Shopify introduced the AI Store Builder to help merchants streamline text-image formatting and page design, thereby reducing resource requirements.⁹ Amazon also launched Project

Starfish to enable third-party sellers to enhance product content through AI, which is projected to add \$7.5 billion in gross merchandise value to the platform in 2025.¹⁰ These cases demonstrate that platform-enabled AI technology sharing can significantly enhance retailer operational efficiency.

However, for e-commerce platforms, the development and deployment of AI do not always yield these anticipated benefits, as they face several key challenges. First, AI development incurs substantial costs. According to research by Guido, most companies allocate over 80% of their total funding to AI computing resources. Furthermore, data from the Dell'Oro Group indicates that in 2022, the world's top ten cloud service providers (including Alibaba, Amazon, and Apple) invested \$114 billion in AI data centre infrastructure. This was their largest expenditure category. Second, AI applications have shown promise in improving consumer shopping experiences (He, Wang, et al. 2024; Q. Wang, Ji, and Zhao 2024; Xu et al. 2023). However, their effectiveness remains uncertain due to challenges such as poor-quality AI recommendation engines and customer service systems. These issues may undermine user satisfaction and harm platform reputation (Ding et al. 2025; Mohammadi et al. 2024). Additionally, sharing AI technology could potentially weaken a platform's competitive advantage by elevating competitors' capabilities. Although AI can improve operational efficiency for retailers, it may also decrease the market competitiveness of a platform's private-label brands. This, in turn, could undermine the platform's position in the industry. For instance, Huawei ceased sharing its technology after recognising the negative impact on the competitiveness of its own products.¹¹ Considering these challenges faced by e-commerce platforms regarding AI development and sharing strategies, this paper studies the following research questions:

- Given the substantial costs associated with AI development, under what conditions can an e-commerce platform achieve profitability by implementing AI technologies?
- In the context of brand competition between national brand and private label products, should platform share their AI technology with a retailer selling competing branded products? Additionally, how does the retailer benefit from the AI solutions provided by this platform?
- Does an improvement in operational service levels due to AI always guarantee platform profitability, and does a decline in service levels caused by AI always lead to reduced profits for supply chain members?

- How do variations in brand advantages and strategies regarding AI technology sharing influence a platform's decision-making about AI technology deployment?

To address these issues, this study constructs a two-stage supply chain game model involving a retailer and an e-commerce platform. The retailer sells national brand (NB) products on the platform, while the platform sells private-label (PL) products, creating direct competition with NB. To enhance consumer purchase intentions, both the platform and the retailer provide services with different operational service costs to improve service quality. Additionally, the platform can choose to adopt and share AI technology to potentially enhance the service level and reduce operational expenses. We examine three scenarios within the base model: (1) The platform does not adopt AI technology (Model NA), (2) the platform adopts AI technology but does not share it with the retailer (Model PA), and (3) the platform adopts and shares AI technology with the retailer (Model DA). Furthermore, our extended analysis explores the impact of varying brand preferences and different AI-sharing strategies (AI fully replaces traditional operational service, incomplete AI technology sharing) under special cases.

The key findings are as follows: (1) Addressing the first research question, we show that the platform's gains from AI technology are attainable only under low R&D costs. Notably, the platform's AI adoption may lead to a lose-lose scenario for supply chain participants due to AI's 'Negative Synergy': High AI R&D costs reduce the platform's profitability without enabling the retailer to benefit from intensified competition, resulting in a lose-lose outcome for both firms. (2) Addressing the second research question, we find that when AI R&D costs are relatively low, the platform's sharing of AI technology may paradoxically reduce both PL demand and overall market size. Nevertheless, such sharing can still yield a win-win outcome for both firms, thereby motivating the platform to engage in AI sharing. (3) Addressing the third research question, we find that improvements in AI service levels do not necessarily ensure platform profitability. Factors such as low consumer trust in PL products or high R&D costs from developing overly advanced AI services can still erode profits. On the other hand, reducing AI service levels may sometimes lead to win-win situations for supply chain members by significantly cutting costs. Additionally, changes in consumer perceptions and the functional role of AI technology can further influence these results. (4) In addressing the last issue, brand advantage differences do not affect the platform's AI adoption decision but do influence profitability margins among supply chain members. In some cases, private-label products are fully replaced by national brands. When this

happens, the retailer benefits from a 'free-riding' effect if the platform adopts AI, potentially harming the platform's profitability. When AI fully replaces traditional services, intensified product competition from AI sharing introduces complex strategic dynamics. Interestingly, a partial AI sharing strategy by the platform may paradoxically reduce its own profitability.

This study makes several theoretical and managerial contributions: First, unlike existing studies that examine standalone AI technologies without systemic integration, our research investigates their impact within a broader framework. We analyze how AI influences platform and retailer decision-making across operational services and technology-sharing strategies. The model considers changes in operational service costs and consumer service/satisfaction (for better or worse), thus addressing a critical research gap. Second, this study analyzes how disparities in brand advantage and cost pressures influence platform AI decisions, providing theoretical guidance for e-commerce platforms to develop AI strategies under different market conditions. Finally, the findings present new insights not previously identified in the literature. For instance, although AI technology can enhance service levels and reduce costs, low consumer trust in PL products or excessive investment in advanced AI services may reduce profits if returns do not offset costs. Therefore, platforms should adjust their AI investments based on market conditions rather than indiscriminately pursuing high technological sophistication.

The remainder of this paper is organised as follows: Section 2 reviews the relevant literature. Section 3 develops and describes the base model. In Section 4, we examine the conditions and effects of AI adoption by the platform. Section 5 explores the AI-sharing strategy and its potential effects on supply chain participants. Section 6 presents four extended models to test the robustness of key findings under different influencing factors. Section 7 concludes the paper and outlines future research directions. All mathematical expressions for the thresholds referenced in the paper, along with the proofs, are provided in Appendices A and B.

2. Literature review

2.1. AI adoption in supply chain management

Recent academic research has increasingly focussed on the adoption of artificial intelligence (AI) technologies in supply chain management. Shahzadi et al. (2024) conducted a systematic review of 68 studies, identifying the drivers of AI adoption from technological, organisational, environmental, and human perspectives, and examining barriers related to technology, organisation,

economy, and workforce. Their analysis highlights the positive impact of AI on operational, environmental, social, and economic dimensions. In the upstream supply chain, AI mainly enhances cost optimisation and efficiency. Jauhar et al. (2024) noted that AI-driven inventory management solutions greatly bolster supply chain resilience. Niu, Dong, and Xie (2026) found that AI improves production yield in cross-border supply chains under standardised high-quality control conditions. Kuo and Choi (2024) demonstrated that AI applications in transportation and logistics significantly enhance operational efficiency. Downstream, generative AI technologies affect consumer purchasing decisions (Lee and Chung 2024) and operational decisions of supply chain participants. Niu, Yu, and Dong (2023) explored a new AI-powered live-streaming business model in cross-border supply chains, showing how global brands balance AI technologies and key opinion leader (KOL) live streaming. Xu et al. (2023) found that AI adoption in dual-channel supply chains can increase manufacturer profits under low network effects. He, Wang, et al. (2024) analysed the interaction between customer service strategies (human vs. AI-driven) and sales models (agency vs. reselling), concluding that AI-driven services are more suitable for the reselling model. Q. Wang, Ji, and Zhao (2024) investigated AI-powered showroom technologies in platform retailing, showing that these technologies enhance performance and mitigate the negative impact of consumer returns. While existing literature predominantly examines singular effects of AI technology, this study simultaneously investigates its dual impact on both operational cost reduction and changes in consumer purchasing intentions.

However, some studies highlight that AI in supply chain management does not always yield positive outcomes. Mohammadi et al. (2024) argued that explainable AI (XAI) might not be the socially optimal choice and could damage firm-consumer trust. Y. Wang et al. (2025) analysed AI's impact from both upstream and downstream perspectives, concluding that retailers might avoid implementing AI even if manufacturers are adopting it. Yu and Guo (2024) emphasised the need to balance high-quality human services and low-cost AI-driven services for corporate profitability. Prior studies have examined the dual role of AI. They show that AI technologies can enhance operational efficiency. At the same time, they may generate consumer aversion (Bockstedt and Buckman 2025; Ding et al. 2025). Building on this literature, our study also explores the dual impact of AI's reducing costs and reshaping consumer perceptions of service. Distinct from prior research, we investigate how AI-driven service levels may either enhance or diminish operational service quality. Additionally, we

examine how AI adoption affects supply chain profitability and influences brand competition, which provides a fresh perspective on AI's overall effects in supply chain management.

2.2. Service operational strategies for e-commerce platforms

Existing literature has explored e-commerce platform service operations from various perspectives, including logistics services (G. Li et al. 2025), pre-sales services (Zhen and Xu 2022), and after-sales services (Radhi and Zhang 2019). In logistics services, scholars have examined last-mile delivery improvements and different service models (Qin et al. 2025), highlighting cost as a critical factor in the selection of service models (Pahwa and Jaller 2022). Asawawibul et al. (2025) summarised the influence of cost on customer satisfaction in e-commerce logistics, considering service quality, technological advancements, and transportation conditions. These studies underscore the importance of cost reduction in e-commerce service operations.

In this paper, we focus on pre-sales service efforts on e-commerce platforms. D. Li et al. (2021) found that investment in operational services can enhance consumer purchase intention and improve supply chain performance. He, Shang, et al. (2024) examined operational investment decisions in social commerce platforms. They designed optimal strategies and coordination mechanisms for brand owners. Ha, Tong, and Wang (2022) found that e-retailers can increase consumer willingness to pay by enhancing service efforts under different power structures. Some scholars have examined customer-centric service policies. They focus on how practices such as return management and quality control influence consumer behaviour (Niu, Dong, and Xie 2026; Qiu et al. 2025). Other studies have explored ways to improve service quality within supply chains (D. Wang et al. 2023; Zhou, Gao, and Zhang 2024). Prior research has mainly focussed on the impact of a single service on a single product, with limited discussions on service strategies in the context of product competition. Additionally, studies on service strategies under information-sharing mechanisms have shown that sharing demand information can shift platform preferences (Lin, Chen, and Xiong 2024; Zhu et al. 2023). In contrast, our study investigates how technology sharing influences platform service strategies, providing a novel perspective.

2.3. Brand competition in e-commerce platforms

In recent years, research on brand competition has primarily focussed on product quality (Luo, Zhong, and Nie 2022). Additionally, scholars have examined

how supply chain members' brand decisions influence competition. Studies on supplier decision-making have explored channel encroachment and how shifts in quality and power structure impact brand competition (Tang, Sethi, and Wang 2023; Z. Zhang et al. 2021). Manufacturers' strategies regarding product information sharing and direct sales channels have also been key areas of interest (Shi et al. 2023). Platform brand strategies mainly involve PLs, that is a core aspect of this study.

Existing research on PLs has focussed on channel strategies (H. Li et al. 2023) and demand information sharing (K. Chen et al. 2024). X. Li, Cai, and Chen (2022) analysed the cost-quality trade-off between low-quality and high-quality PLs, revealing retailers' optimal encroachment decisions. Long and Amaldoss (2024) examined the impact of platform-sponsored advertising on PLs. They found that when advertising significantly boosts demand, PLs are not always the optimal choice for consumers. B. Liao, Yano, and Trivedi (2020) studied PL quality positioning across different procurement and pricing structures, characterising optimal decisions under various scenarios. X. Zhang and Hou (2022) compared PL sales models from a sustainability perspective, identifying key factors for optimal models. Y. Wang, Ha, and Tong (2022) focussed on private demand information sharing, offering insights into how brand service effort competition influences supply chain information-sharing incentives. However, the impact of advanced technologies, such as AI adoption for cost efficiency and operational services, on PLs remains underexplored. Gielens et al. (2021) highlighted how retailers can use data and technological marketing to develop intelligent PLs, enhancing differentiation, store loyalty, and profitability. Unlike traditional investments in product quality, this study focuses on how technological investments alter supply chain members' decision-making behaviours and transform product competition dynamics. In contrast to prior research, we incorporate cost, service, and different sharing strategies within the context of brand competition. These factors have rarely been examined together in the existing literature. By combining them, our study offers a novel perspective on private-label research.

2.4. Research gap

This study differs from existing literature in three key aspects, highlighting its innovation and theoretical contributions. First, while substantial research exists on AI-driven supply chain management, most studies focus on singular effects of AI, failing to reveal its dual impact on cost reduction and consumer purchase intention. Although Y. Wang et al. (2025) examined AI applications

across the supply chain, they did not analyze the varying impacts of AI technology adoption on competitive and cooperative relationships among firms. Additionally, prior studies only considered AI's cost-saving effect, which may impact consumer purchase intention. Our analysis goes further by incorporating the cost-saving effect alongside the dual influence of AI technology. Specifically, we examine how AI can both enhance and diminish operational service levels, thereby affecting consumers' purchase intentions. Second, research on the interaction between platform brand competition and operational service investment is limited. This study systematically explores how different service models and scenarios shape brand competition mechanisms within the supply chain. Finally, while existing studies have separately investigated operational services, technology sharing, and PLs' effect on decision-making, few have examined their interplay. This study fills that gap by offering a holistic perspective on their combined impact. Table 1 summarises the research gaps between our study and related literature.

3. Model setup

This study develops a two-stage supply chain model consisting of a retailer and an e-commerce platform. In this model, the retailer (referred to as 'she') employs an agency model to sell an NB product on the e-commerce platform (referred to as 'he'). Under the agency model, the retailer pays an agency fee f to the e-commerce platform while retaining the autonomy to set the retail price p_R independently (H. Li et al. 2023). Concurrently, the e-commerce platform sells its own PL product at the price p_E , which directly competes with the retailer's NB product. For simplicity, we assume zero marginal costs for both products (C. Liao et al. 2025; X. Li, Cai, and Chen 2022).

Consumers demonstrate diverse preferences for various products, resulting in differing valuations in the marketplace (B. Liao, Yano, and Trivedi 2020; Long and Amaldoss 2024). For the NB product, a consumer's valuation is determined by their willingness to pay, represented by v , which follows a uniform distribution over the interval $[0, 1]$. As noted by Gielens et al. (2021), consumers generally perceive PLs as lower-tier substitutes for NBs, leading to a reduced valuation for PL products. To address this preference and perception gap, we introduce a preference parameter $0 < \theta < 1$ to reflect a consumer's lower perception of PL products, expressed as θv . This assumption of a preference parameter in the range $[0, 1]$ captures the competitive dynamics between PLs and NBs, which is a theme extensively explored in supply chain literature (C. Liao et al. 2025; H. Li et al. 2023; X. Zhang and

Table 1. Comparisons of our paper and the related literature.

Researches	AI adoption			
	reducing operational costs	influencing consumer behaviour	operation service strategies	brand competition
Mohammadi et al. (2024)		✓		
Ding et al. (2025)	✓	✓	✓	
Xu et al. (2023)		✓	✓	
Yu and Guo (2024)	✓		✓	
Y. Wang et al. (2025)	✓	✓	✓	
D. Li et al. (2021)			✓	✓
Long and Amaldoss (2024)			✓	✓
This study	✓	✓	✓	✓

Hou 2022). Consumers typically exhibit stronger purchase preferences for NBs over PLs (Gielens et al. 2021; Z. Zhang et al. 2021). In some cases, such as Walmart, PLs account for over half of total profits, a level of profitability that far surpasses that of NBs. In such cases, consumers may exhibit stronger purchase preferences for PLs over NBs.¹² The scenario in which consumers perceive PLs as superior to NBs will be further explored in Sections 6.1, and 6.2 characterises the market scenario in which NBs completely supplant PLs. We assume that each consumer purchases at most one unit, either an NB product, a PL product, or none at all.

In practice, many e-commerce platforms, including JD.com and Amazon, allocate substantial resources to customer service to enhance satisfaction and increase customers' willingness to pay (Ha, Tong, and Wang 2022; H. Li et al. 2023). In our model, the value-added efforts of both the platform and the retailer, such as personalised recommendations and after-sales services, are quantified as service level s . However, these investments also incur additional operational service costs for both firms, requiring the retailer and platform to incur service-related costs. We assume that the retailer and the platform must incur a per-unit service cost of c_R and c_E , respectively. This modelling of service levels and their corresponding costs aligns with the assumptions adopted in prior studies (He, Wang, et al., 2024). Although the platform provides services s through a unified sales channel, consumers' lower trust in PL products leads to a diminished perception of the operational services for PLs. Prior studies have shown that even when the service level of PL products matches that of NBs, consumers still perceive lower service quality for PLs due to weaker brand trust (Beneke et al. 2013; Hwang, Lee, and Park 2021). Therefore, we model the incremental utility derived from services provided on the platform to a PL product as θs (C. Liao et al. 2025; H. Li et al. 2023). Consequently, we define consumer utilities from purchasing NB products and PL products as follows:

$$U_R = v - p_R + s, \quad U_E = \theta(v + s) - p_E.$$

As discussed in Section 1, e-commerce platforms can leverage AI technologies to reduce operational service costs and decide whether to share these technologies with retailers. AI has been widely adopted in e-commerce, enabling more precise and efficient product matching, thereby enhancing consumers' willingness to purchase (Q. Wang, Ji, and Zhao 2024). However, immature AI applications may reduce consumer willingness to buy or even deteriorate the shopping experience (Mohammadi et al. 2024; Yu and Guo 2024). For example, Alibaba's Taobao AI-powered customer service system has faced widespread consumer criticism due to poor service quality. Despite the potential deterioration in consumer shopping experience resulting from the adoption of AI technologies, firms may still be incentivised to implement these technologies in order to reduce operational service costs and improve overall profitability (Y. Wang et al. 2025; Yu and Guo 2024). In practice, platforms such as Shopify provide AI tools (e.g. Sidekick or Magic) with various functional tiers. This allows the platform to decide both the activation and the extent of particular AI service levels.¹³ Likewise, the Sellful platform offers modular AI-based features, enabling consumers to experience adjustable service quality.¹⁴ Following Niu, Yu, and Dong (2023) and He, Wang, et al. (2024), we assume that s_A represents the service level of the platform after applying AI technology, referred to as the AI service level. It is worth noting that while s_A introduces AI-based automated services, it still retains part of the traditional operational services, which may result in either higher or lower perceived service levels. Consequently, in our baseline model, we assume that consumers' perceived service quality transitions from s to s_A (D. Li et al. 2021). Furthermore, we extend the model in Subsection 6.5 to include scenarios where some consumers continue to prefer traditional human-based services. Therefore, when the e-commerce platform applies AI technology exclusively to its PL products, the consumer utilities for NB and PL products are defined as $U_R = v - p_R + s$ and $U_E = \theta(v + s_A) - p_E$, respectively. If the platform shares AI technology with the retailer and

Table 2. Notations and descriptions.

Notations	Descriptions
p_E	Platform's PL product price (decision variable)
p_R	Retailer's NB product price (decision variable)
f	Agency fee charged by the platform to the retailer (decision variable)
s_A	AI operational service level (decision variable)
v	Consumer's purchase valuation, it follows uniform distribution in $[0, 1]$
θ	Consumer preference for PL, $0 < \theta < 1$
s	Traditional operational service level
k	Cost coefficient of AI technology R&D
β	Coefficient by which AI technology reduces operational service cost
c_i	Platform's and retailer's operational service costs ($i = E, R$)
Π_i	Platform's and retailer's profit function ($i = E, R$)

both firms replace traditional services with AI-provided services, the consumer utilities become $U_R = v - p_R + s_A$ and $U_E = \theta(v + s_A) - p_E$. To simplify the analysis, our baseline model assumes that if the platform shares AI technology, the platform fully shares its AI technology with the retailer. We explore scenarios with incomplete technology sharing in Section 6.

The advancement of AI technology can significantly reduce operational service costs for both the platform and the retailer, thereby lowering their per-unit operational service cost. We assume that replacing traditional services with AI services reduces the original unit operational service cost by $c_i - \beta s_A$, where $i = R$ and $i = E$, and β represents the sensitivity coefficient of AI in reducing operational service costs. Here, $\beta \in [0, \frac{c_i}{s_A}]$ to ensure the feasibility of the parameters, which is consistent with the considerations made in existing similar studies by Y. Wang et al. (2025) and He, Wang, et al. (2024). In Section 6.3, we further examine scenarios where AI services fully eliminate operational service costs for firms. However, implementing AI technology requires the platform to incur R&D costs, modelled as $\frac{ks_A^2}{2}$, where k represents the cost coefficient of AI development. The high R&D costs associated with AI may outweigh its benefits, making it crucial for the platform to carefully evaluate the trade-offs to achieve profit maximisation. In the analysis that follows, we assume $k_0 < k < k_4$ to focus on feasible scenarios with non-negative prices and demands. Table 2 summarises the definitions of all parameters used in this study.

Based on the aforementioned assumptions, we consider three scenarios within the baseline model: the e-commerce platform does not adopt AI technology (Model NA); the e-commerce platform adopts AI technology exclusively to its PL products (Model PA); and the platform adopts AI technology and shares it with the retailer (Model DA). The sequence of events and decisions in the supply chain is as follows (as illustrated in Figure 1):

- The e-commerce platform decides whether to adopt AI technology, then he determines the AI service level s_A .
- The e-commerce platform decides whether to share AI technology, and the retailer decides whether to accept it.
- The e-commerce platform sets the commission rate f charged to the retailer.
- The e-commerce platform and the retailer simultaneously determine their respective product prices, p_E and p_R .

4. AI adoption strategies

4.1. Analysis of model NA and model PA

In the baseline scenario of the Model NA, the e-commerce platform employs a traditional, non-AI-driven operational service model and competes with the retailer's NBs by selling its own PLs. The market demand for the PLs and the NBs is expressed as follows: $q_E = \frac{p_R - p_E + \theta s - s}{1 - \theta} - \frac{p_E - \theta s}{\theta}$ and $q_R = 1 - \frac{p_R - p_E + \theta s - s}{1 - \theta}$, respectively. In this model, both the platform and the retailer incur traditional operational service costs c_i . The profit functions for the supply chain members are formulated as follows: $\pi_E = f q_R + (p_E - c_E) q_E$, $\pi_R = (p_R - f - c_R) q_R$. Using backward induction, we obtain the equilibrium solutions for Model NA, and the derivation of all the results and the mathematical expressions are presented in the appendix.

In Model PA, the platform leverages AI technology to provide service for its PL product while simultaneously reducing its operational service costs, despite incurring additional AI development expenses. In this scenario, the market demand for NB and PL products is given by $q_R = 1 - \frac{p_R - p_E + \theta s_A - s}{1 - \theta}$ and $q_E = \frac{p_R - p_E + \theta s_A - s}{1 - \theta} - \frac{p_E - \theta s_A}{\theta}$, respectively. In model PA, the profit functions for the supply chain members are expressed as follows: $\pi_E = f q_R + (p_E - (c_E - \beta s_A)) q_E - \frac{ks_A^2}{2}$, $\pi_R = (p_R - f - c_R) q_R$. Lemma 4.1 shows how the equilibrium outcomes are affected by the cost coefficient of AI technology k .

Lemma 4.1: $\frac{\partial s_A^{PA}}{\partial k} < 0$, $\frac{\partial f^{PA}}{\partial k} < 0$, $\frac{\partial p_R^{PA}}{\partial k} > 0$, $\frac{\partial p_E^{PA}}{\partial k} < 0$, $\frac{\partial q_R^{PA}}{\partial k} > 0$, $\frac{\partial q_E^{PA}}{\partial k} < 0$, $\frac{\partial \Pi_E^{PA}}{\partial k} < 0$, $\frac{\partial \Pi_R^{PA}}{\partial k} > 0$.

Lemma 4.1 indicates that the platform's AI adoption level, the commission fee charged to the retailer, as well as the price, demand, and profitability of PL products, are negatively correlated with the cost coefficient of AI technology adoption. Conversely, the price,

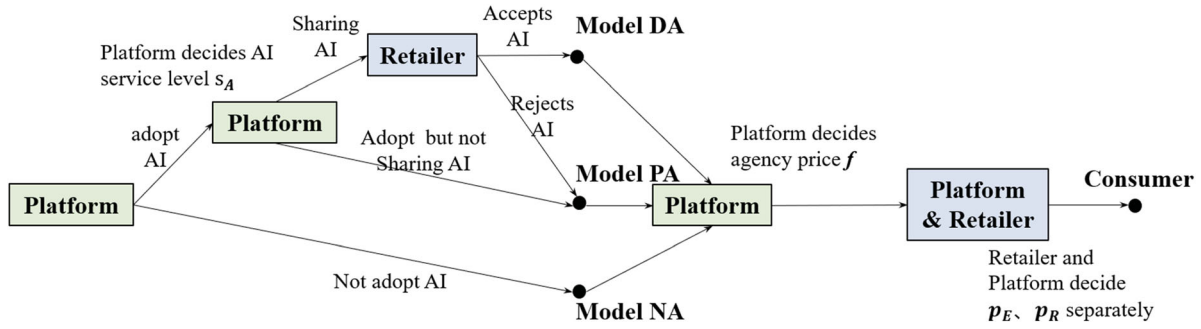


Figure 1. The sequence of events.

demand, and profitability of NB products are positively correlated with this cost coefficient. As the cost of adopting AI technology increases, the platform reduces its AI service level to maintain profit margins, leading to a decrease in consumer interest and demand for PL products. Consequently, consumers increasingly favour NB products, prompting the platform to lower the prices of PL products to remain competitive. In this context, both demand and prices for NB products rise with the increasing AI R&D cost coefficient. Ultimately, the platform's profitability declines as the AI R&D cost coefficient increases, while the retailer's profitability increases.

4.2. Comparative analysis of model PA and model NA

In this section, we analyze the impact of AI technology adoption on PLs by comparing the outcomes of Model NA and Model PA. Corollary 4.1 first illustrates how AI technology affects both the pricing of products and demand of supply chain members.

Corollary 4.1: (1) When $k \geq k_1$: then $p_R^{PA} \geq p_R^{NA}$, $q_R^{PA} \geq q_R^{NA}$; otherwise $p_R^{PA} < p_R^{NA}$, $q_R^{PA} < q_R^{NA}$.
 (2) When $k \leq k_1$: then $f^{PA} \geq f^{NA}$, $q_E^{PA} \geq q_E^{NA}$; otherwise $f^{PA} < f^{NA}$, $q_E^{PA} < q_E^{NA}$.
 (3) When $k \leq k_2$: then $p_E^{PA} \geq p_E^{NA}$; otherwise $p_E^{PA} < p_E^{NA}$.

Corollary 4.1 indicates that when the AI R&D cost coefficient is sufficiently high, both the price and demand for NBs increase when platform adopts AI services for its PL products. This occurs because high AI R&D costs lead the platform to reduce its AI service level, weakening PL product. Consequently, PL products lack differentiation, forcing the platform to lower PL prices to compete with NB products. Furthermore, even when the retailer raises the price of NB products, the retailer can still maintain strong market competitiveness. The platform is burdened by high AI R&D costs and earns minimal profits from PL

products. To ensure revenue stability, it reduces commission fees to promote the retailer's NB product sales. Conversely, low AI R&D costs enable the platform to enhance AI service level s_A , improving consumer purchase intention and the competitiveness of PL products. This boosts PL demand and allows the platform to set higher PL prices due to reduced operational service costs. The service enhancement and aggressive pricing of PL products reduce the market share of NBs. The retailer is compelled to lower NB prices, yet demand still declines due to their inferior service level. As PL products become more competitive, the platform relies less on the retailer for profit and raises the commission fee, which the retailer must accept to sustain sales.

Corollary 4.2: When the platform applies AI technology exclusively to its PL products and the AI R&D cost coefficient is relatively low (i.e., $k < k_1$), the adoption of AI technology can increase total market demand.

Corollary 4.2 shows that low AI R&D costs can lead to an overall market expansion. The platform attracts consumers from NB products to PL products while activating latent demand, thereby drawing in previously non-participating consumers. The improvement in PL services increases the platform's overall attractiveness (e.g. JD.com's enhanced logistics boosts site-wide traffic). As a result, the decrease in NB demand q_R^{PA} is smaller than the increase in PL demand q_E^{PA} , resulting in overall market growth.

Proposition 4.1: When the platform applies AI technology exclusively to its PL products:

- (1) The platform is better off from AI adoption only when the AI R&D cost coefficient is relatively low (i.e. $k < k_3$).
- (2) The retailer is better off from platform's AI adoption only when the AI R&D cost coefficient is relatively high (i.e. $k_1 < k < k_4$, where $k_3 < k_1$).

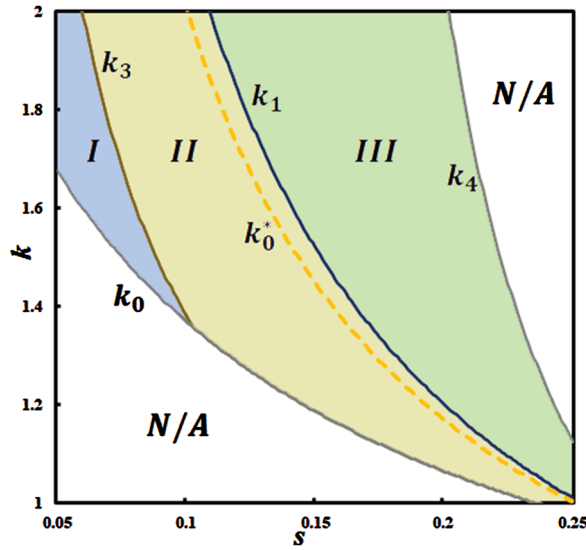


Figure 2. The strategic preferences after adopting AI ($\theta = 0.7, c_R = 0.5, c_E = 0.3, b = 0.1$).

Proposition 4.1 states that when the AI R&D cost coefficient is low ($k < k_3$), the platform incurs minimal AI R&D expenses, enabling the significant adoption of AI technology to enhance service quality and reduce operational service costs. This boosts the competitiveness of PL products, allowing the platform to increase product prices p_E while driving an increase in demand. The platform also extracts higher profits from the retailer through increased agency fees, thereby expanding its earnings. However, the strengthened competitiveness of PLs reduces retailer profitability (illustrated in Region I of Figure 2). On the other hand, when the AI R&D cost coefficient is high ($k_1 < k < k_4$), the platform limits AI investment to control costs, decreasing PL product competitiveness and platform profits. Yet, the retailer benefits from lower agency fees, demand reshoring, and higher product prices (shown in Region III of Figure 2). Thus, critical threshold values (e.g. k_1 and k_3) represent the points at which the incremental benefit from enhancing service quality is outweighed by the burden imposed by increasing R&D costs. This dynamic triggers a reversal in platform and retailer profit, thereby delineating distinct profit regions.

This study uncovers a counterintuitive phenomenon: when the AI R&D cost coefficient is within a critical range ($k_3 < k < k_1$), AI adoption leads to a systemic decline in overall supply chain profitability. This occurs because of the differing sensitivities of the platform and retailer to AI-driven advantages. High AI R&D costs reduce the platform's profitability without enabling the retailer to benefit from intensified competition, resulting in losses for both firms. This asynchronous profit shift is termed 'Negative Synergy'. This phenomenon is illustrated in

Region II of Figure 2. We further analyze how variations in AI service levels affect the profitability of supply chain members. The results show that the platform captures gains from AI adoption only when the AI service level surpasses that of traditional operational services (i.e. $k < k_0^*$, where $k_3 < k_0^* < k_1$). However, a higher AI service level may also reduce the platform's profit (when $k_3 < k < k_0^*$). In contrast, the retailer benefits from the platform's use of AI technology only when the AI service level is inferior to that of traditional services (when $k > k_0^*$). These results indicate that platforms should carefully evaluate both the service level and the associated costs of AI technologies to avoid a decline in profit. In fact, Amazon's AI-based advertising recommendation system has forced sellers to increase agency expenditures, often leading to losses. Meanwhile, the platform itself has seen reduced sales due to additional operating costs. The threshold effect we identify thus provides a theoretical basis for platforms to balance their interests with partners.

5. AI sharing strategies

5.1. Analysis of model DA

In Model DA, the e-commerce platform shares AI technology with the retailer, resulting in shifts of consumer purchase preferences between NB and PL products. The demand for these products are expressed as $q_R = 1 - \frac{p_R - p_E + \theta s_A - s_A}{1 - \theta}$ for the retailer's product, and $q_E = \frac{p_R - p_E + \theta s_A - s_A}{1 - \theta} - \frac{p_E - \theta s_A}{\theta}$ for the platform's product. Furthermore, the operational service costs for both products are reduced. Under these circumstances, the profit functions for the supply chain members are defined as follows: $\pi_E = f q_R + (p_E - (c_E - \beta s_A)) q_E - \frac{k s_A^2}{2}$, $\pi_R = (p_R - f - (c_R - \beta s_A)) q_R$. By applying the backward-solving approach, we obtain the equilibrium solutions for the components in model DA, as shown in the appendix.

Lemma 5.1: $\frac{\partial s_A^{DA}}{\partial k} < 0$, $\frac{\partial f^{DA}}{\partial k} < 0$, $\frac{\partial p_R^{DA}}{\partial k} < 0$, $\frac{\partial p_E^{DA}}{\partial k} < 0$, $\frac{\partial q_R^{DA}}{\partial k} < 0$, $\frac{\partial q_E^{DA}}{\partial k} < 0$, $\frac{\partial \Pi_E^{DA}}{\partial k} < 0$, $\frac{\partial \Pi_R^{DA}}{\partial k} < 0$.

Lemma 5.1 demonstrates that as the platform shares AI technology, the adoption level, commission charged to the retailer, and price, demand, and profit of supply chain members all exhibit negative correlations with the AI R&D cost coefficient. When the platform adopts AI technology and shares it with the retailer, the changes in key metrics for the platform and PL products are similar to Lemma 4.1. However, for the retailer, as the AI R&D cost coefficient rises, NB products face heightened competition and weakened consumer purchase intention,

leading to a loss in demand. To maintain market attractiveness, the retailer must lower prices, which reduces profitability. These findings highlight that increased AI R&D costs trigger a chain reaction of declining prices and demand through changes in operational service costs, market competitive dynamics, and demand elasticity. Consequently, the platform reduces both AI investment and commission fees, thereby amplifying the downward pressure on supply chain prices and demand. This underscores the critical role of AI and technology cost management in supply chain competition, emphasising the need for firms to establish a refined cost-benefit management system to mitigate the risk of profit erosion in high-cost environments.

5.2. Comparative analysis of model DA and model PA

In model DA, to ensure all optimal solutions remain non-negative, we impose an upper bound for AI cost coefficient (i.e. $k < \tilde{k}_0$). Proposition 5.1 shows the changes in AI service level and agency fee following the platform's sharing of its AI technology.

Proposition 5.1: *When $k < k_0^*$, then $s_A^{DA} > s_A^{PA} > s$; When $k_0^* \leq k \leq \tilde{k}_0^*$, then $s_A^{DA} \geq s \geq s_A^{PA}$; When $k > \tilde{k}_0^*$, then $s > s_A^{DA} > s_A^{PA}$.*

Proposition 5.1 indicates that a lower AI R&D cost coefficient allows the platform to achieve a relatively high AI technology level without incurring excessive costs, in which case the AI service level surpasses that of traditional services. However, when cost pressures are substantial, the platform adopts an AI technology level below the traditional benchmark. Moreover, when the platform shares its AI technology, an increased AI service level s_A simultaneously enhances the competitiveness of both PL and NB products, creating a synergistic demand increase. Compared with Model PA, Model DA yields higher marginal returns on AI investment (as it stimulates demand for both PL and NB products). In this case, the retailer benefits from AI-induced cost reductions and increased profitability, while the platform can offset AI R&D costs by charging higher commission fees f , mitigating the cost of increasing s_A . Thus, the synergy in demand and cost savings ensures that the platform's AI service level s_A tends to rise when AI is shared (i.e. $s_A^{DA} > s_A^{PA}$). As the cost of AI R&D crosses critical thresholds, the trade-off between marginal benefits and marginal costs undergoes significant shifts, resulting in adjustments to the optimal level of AI service for the platform. Figures 2 and 3 illustrate the variation in profits of supply chain members when the AI service level is either above or

below the traditional operational service level, under the scenarios of platform adoption and sharing of AI technology. The corresponding explanations are provided in Propositions 4.1 and 5.2.

Corollary 5.1: *Compared to model PA, when the platform shares AI technology (model DA):*

- (1) *The price of the retailer's NB product will increase if and only if $k \leq \tilde{k}_2$.*
- (2) *The price of the platform's PL product will increase if and only if $k \leq \tilde{k}_3$.*

Corollary 5.1 suggests that the impact of AI technology sharing on product pricing is contingent on the AI R&D cost coefficient. When AI R&D costs are low, the platform can use AI to significantly improve the service quality of both PL and NB products, enhancing consumer purchase intent and reducing operational service costs. Consequently, the platform can maximise profits by increasing PL product prices. For the retailer, although NB product competitiveness improves and operational service costs decrease, higher agency fees imposed by the platform capture the benefits driven by AI. The retailer responds by raising the prices of NB products to maintain profitability. On the other hand, when AI R&D costs are high, the platform must reduce its AI investments to sustain profitability, leading to decreased demand for PL products. To boost sales, the platform lowers PL product prices. Although agency fees are reduced, increasing retailer's profit margins, the reduction in operational service costs is limited. Consequently, the retailer decreases NB product prices to expand market share. Thus, under high AI R&D cost conditions, both the platform and the retailer are compelled to reduce prices due to cost constraints, ensuring market position retention.

Corollary 5.2: *Compared to model PA, when the platform shares AI technology (model DA):*

- (1) *The demand for NB products will increase if and only if $k \leq \tilde{k}_4$.*
- (2) *The demand for PL products will increase if and only if $k \geq \tilde{k}_5$.*
- (3) *The total market demand will increase if and only if $k \geq \tilde{k}_6$.*

Corollary 5.2 uncovers an intriguing conclusion. When AI technology is shared and the AI R&D cost coefficient is low, NB products' demand rises, while the demand for PL products and the overall market demand decrease. This occurs because lower AI R&D costs significantly enhance consumer utility for both NB and PL

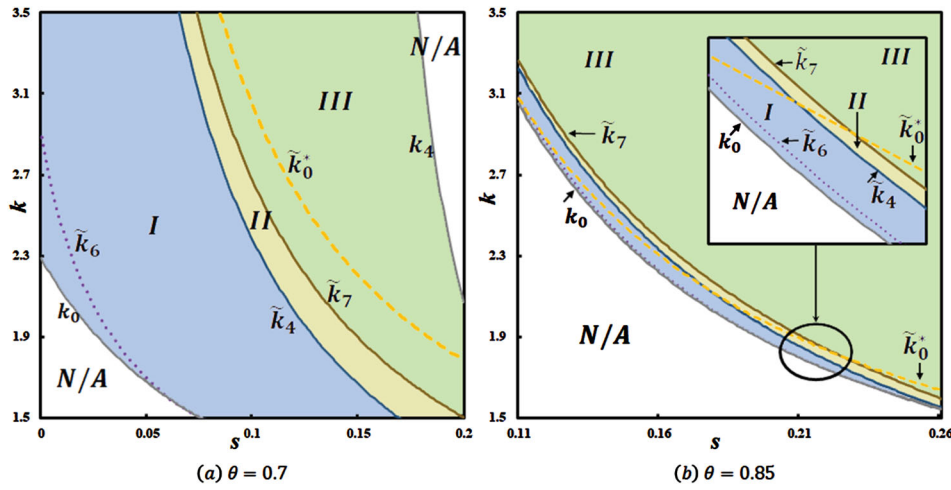


Figure 3. The strategic preferences after sharing AI ($c_R = 0.5, c_E = 0.3, b = 0.1$).

products. However, because of the inherent preference disadvantage of PL products ($\theta < 1$), consumer willingness to purchase NB products increases more sharply. Consequently, NB products become more competitive, drawing consumers away from PL products, thus reducing PL demand but boosting NB demand. Both the platform and the retailer raise prices to maximise profits due to this technological edge. Nevertheless, intensified price competition excludes some low-willingness-to-pay consumers. This leads to a larger decline in PL demand and an overall market contraction, reducing total market demand. Conversely, when AI R&D costs are high, the platform's AI investment is limited, which reduces consumer willingness to purchase. In response, both the platform and the retailer lower prices to maintain market share. However, the retailer still has limited capacity to reduce prices due to their ongoing agency fee obligations. As a result, some NB demand shifts to more affordably priced PL products, decreasing NB demand while increasing PL demand. Additionally, lower prices attract more price-sensitive consumers, expanding overall market demand despite individual product demand fluctuations due to price reductions and increased market penetration.

- Proposition 5.2:** (1) *The retailer accepts the platform's AI technology sharing only when the AI R&D cost coefficient is relatively low (i.e. $k \leq \tilde{k}_4$).*
- (2) *The platform will engage in AI technology sharing only when the AI R&D cost coefficient is relatively low (i.e. $k \leq \tilde{k}_7$, where $\tilde{k}_4 < \tilde{k}_7$).*

Proposition 5.2 suggests that when the platform shares AI technology and the AI R&D cost coefficient is low, the retailer can achieve higher profits due to increased NB

product prices and demand, as well as savings in operational service costs. This is despite the higher agency fees. Simultaneously, although PL product demand and overall market demand decrease, the platform still secures higher marginal profits through PL price hikes, increased agency fees, and reduced costs. Conversely, when the AI R&D cost coefficient is high, the platform faces significant cost pressure, and reductions in product prices and agency fees that lead to reduced revenue from both product prices and agency fees. Although the market expands, declining marginal profitability ultimately reduces platform income, while the retailer suffers from lower product prices and diminished market demand. Under these conditions, the platform will not share its AI technology, nor will the retailer accept it. These threshold intervals represent the balance between the demand-expansion effect induced by AI technology and the cost-pressure effect associated with AI R&D. A transition in the dominant effect leads to structural adjustments in the optimal strategies and profit outcomes of both the platform and the retailer, shifting from win-win to lose-lose scenarios across threshold-defined regions.

Figure 3 provides a clearer illustration of the findings. In Region I, where AI R&D costs are relatively low, both the platform and the retailer can achieve a win-win outcome through AI technology sharing, despite some market contraction indicated when $k < \tilde{k}_6$. As the AI R&D cost coefficient increases (Region II), the retailer's profits begin to decline. Meanwhile, the platform's profits continue to grow because its revenue comes from both PL product sales and agency fees, while the retailer relies solely on product sales. In Region II, while PL profitability is compromised, the platform can sustain profits by strategically adjusting agency fees and reducing product prices. In response, the platform prioritises reducing AI service levels (s_A) to control costs, which leads to a

decline in retailer profits sooner as they lose the cost savings from AI technology. In Region III, with high AI R&D costs, both the platform and the retailer experience profit losses, even though market demand expands. Comparing Figure 3(a,b), a higher preference for PL products (θ) reduces the range in which the platform benefits from AI technology sharing. This shift suggests that increased homogeneous competition is detrimental to the sustainable development of the supply chain. Therefore, platforms should manage AI investments precisely to control costs and focus on differentiating PL brand competition. These conclusions offer managerial insights for firms investing in AI technology. Platforms should determine their AI investment intensity and scope based on market structure.

Furthermore, when consumer trust in PL products is low (Figure 3(a)), both the platform and the retailer can profit from sharing AI technology only if the AI service level exceeds traditional operational services (when $k < \bar{k}_0^*$). This is because the return threshold for the platform investment is high, requiring AI to deliver superior consumer experiences before generating profits. In contrast, when consumer trust in PL products is high (Figure 3(b)), AI-enabled cost reductions can yield a win-win outcome for supply chain members even with declining service levels. However, if traditional service levels are already high, unnecessarily raising AI service levels may instead increase R&D costs and erode supply chain profitability. These findings align with Ding et al. (2025), who demonstrate that AI can enhance profitability through cost savings despite lower service levels, and with Y. Chen et al. (2022), who show that in such environments, the diminishing marginal returns of AI may undermine firm performance.

6. Extension

6.1. Private label possess greater brand advantages

In practice, some platforms have successfully developed PL products that outperform traditional NB products. Additionally, since platforms are closer to consumers than a retailer selling through the platform and can access more consumer data, they are able to provide services more tailored to consumer preferences. Therefore, in this section, we assume that PL products hold a brand advantage over traditional NB products due to these factors. The utility consumers derive from purchasing NB and PL products is expressed as: $U_R = \gamma(v + s) - p_R$, $U_E = v + s - p_E$. Here, $\gamma \in (0, 1)$ represents consumers' preference for NB products, indicating that the utility derived from NB products is lower than that from PL products. This parameter reflects the platform's

product or informational advantage over retailer (K. Chen et al. 2024). The demand for NB and PL products is given by: $q_R = \frac{p_E - p_R + \gamma s - s}{1 - \gamma} - \frac{p_R - \gamma s}{\gamma}$ and $q_E = 1 - \frac{p_E - p_R + \gamma s - s}{1 - \gamma}$. When AI technology is implemented and used exclusively by the platform, it leads to changes in consumer demand for NB and PL products as follows: $q_R = \frac{p_E - p_R + \gamma s - s_A}{1 - \gamma} - \frac{p_R - \gamma s}{\gamma}$ and $q_E = 1 - \frac{p_E - p_R + \gamma s - s_A}{1 - \gamma}$. If the platform decides to share AI technology with the retailer, the resulting demand changes to $q_R = \frac{p_E - p_R + \gamma s_A - s_A}{1 - \gamma} - \frac{p_R - \gamma s_A}{\gamma}$ and $q_E = 1 - \frac{p_E - p_R + \gamma s_A - s_A}{1 - \gamma}$.

This section explores three models: Model SNA, where the platform does not adopt AI technology; Model SPA, where the platform adopts but does not share AI technology; and Model SDA, where the platform both adopts and shares AI technology. The profit functions are consistent across these models in terms of structure and formulation. Through a comparative analysis of equilibrium profits of supply chain members of supply chain members across these models, we establish the following proposition:

Proposition 6.1: *If PL products have a stronger brand advantage:*

- (1) *When the platform adopts but does not share AI technology: (i) The platform can profit from adopting AI technology only when the AI R&D cost coefficient is relatively low (i.e. $k < \bar{k}_1$). (ii) The retailer benefits from the platform's adoption of AI technology only when the AI R&D cost coefficient is relatively high (i.e. $k > \bar{k}_2$, where $\bar{k}_1 < \bar{k}_2$).*
- (2) *When the platform shares AI technology: (iii) The platform benefits from AI technology sharing only when AI R&D cost coefficients are relatively low (i.e. $k < \bar{k}_3$). (iv) The retailer benefits from AI technology sharing only when AI R&D cost coefficients are relatively low (i.e. $k < \bar{k}_4$, where $\bar{k}_3 > \bar{k}_4$).*

Proposition 6.1 (1) illustrates that even when the platform's PL products have a stronger market advantage, the profit dynamics among supply chain members are largely consistent with the baseline model, where NB products hold a stronger brand advantage. This suggests that the primary mechanism driving platform profit fluctuations is rooted in cost structures, product pricing, and agency fees. Brand advantage primarily affects threshold conditions and does not fundamentally alter the competitive dynamics of the supply chain platform. Proposition 6.1 (2) further supports our baseline model by showing that varying brand advantages do not fundamentally change the profit dynamics among supply chain members. When PL products have a market advantage, the profit landscape is divided into three regions: at low AI R&D

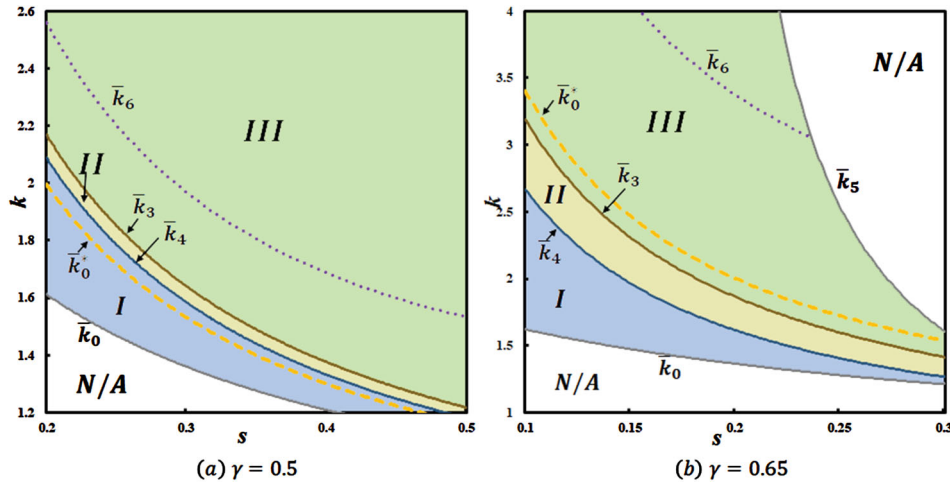


Figure 4. The strategic preferences in a stronger PL brand advantage ($c_R = 0.2, c_E = 0.5, b = 0.1, \gamma = 0.7$).

costs, both the platform and retailer benefit (Region I in Figure 4); at moderate AI R&D costs, only the platform benefits (Region II in Figure 4); and at high AI R&D costs, AI technology sharing reduces profitability for both firms (Region III in Figure 4). AI technology sharing reduces total market demand only at very high AI R&D costs ($k > \bar{k}_6$); otherwise, it expands market demand. This is in contrast to the baseline model, where lower AI R&D costs can lead to market contraction due to intense competition. In PL-dominant markets, the market expansion window for AI technology sharing is broader, with only extremely high costs proving ineffective. By comparing Figure 4(a,b), we observe that when consumer preference for NB products is low (Figure 4(a)), both the platform and the retailer can achieve mutual benefits even if the AI service level falls below that of traditional services ($\bar{k}_0^* < k < \bar{k}_4$). In contrast, when consumer preference for NB products is high (Figure 4(b)), AI adoption may reduce profits for both firms, even when AI enhances service levels ($\bar{k}_3 < k < \bar{k}_0^*$). This indicates that technology collaboration led by a dominant brand is more universally beneficial to supply chain members. Establishing a strong PL brand advantage enhances supply chain resilience against secondary brand fluctuations. Firms should tailor AI technology strategies to their specific brand advantage to maximise profitability and market growth.

6.2. AI adoption in the absence of PL products

In this section, we consider a setting where PLs are absent. In this situation, the platform's revenue relies exclusively on collecting commission fees from the retailer. To maximise profitability, the platform can adopt AI technology to help the retailer reduce operational service costs and boost NB product sales, and increases commission fees to capture greater profits. Specifically,

when the platform does not adopt AI technology, the demand for the NB product is given by $q_R = 1 - p_R + s$. After adopting AI technology, the demand becomes $q_R = 1 - p_R + s_A$. Two scenarios are considered: the platform does not adopt AI technology (Model NNA) and the platform shares AI technology with the retailer (Model NDA). The corresponding profit functions for the supply chain members in each model are as follows:

$$\begin{aligned}\pi_E^{NNA} &= f q_R, & \pi_R^{NNA} &= (p_R - f - c_R) q_R \\ \pi_E^{NDA} &= f q_R - \frac{k s_A^2}{2}, \\ \pi_R^{NDA} &= (p_R - f - (c_R - \beta s_A)) q_R\end{aligned}$$

Using backward induction, we determine the optimal profit outcomes for each scenario, which are summarised in appendix. To guarantee non-negative solutions, the constraint $k > \hat{k}_0 = \frac{(1+\beta)^2}{4}$ must be met. By comparing the outcomes of these scenarios, we derive the following proposition.

Proposition 6.2: *When the platform does not have a PL product: (1) Under low AI R&D costs ($k < \hat{k}_1$), both the platform and the retailer experience a win-win outcome. (2) Under moderate AI R&D costs ($\hat{k}_1 \leq k \leq \hat{k}_2$), the platform incurs losses, while the retailer's profit increases. (3) Under high AI R&D costs ($k > \hat{k}_2$), both the platform and the retailer experience losses.*

Proposition 6.2 indicates that without PL products, the profit distribution between the platform and retailer resembles scenarios where PL products exist. Under low AI R&D costs (Figure 5, Region I), the platform can adopt

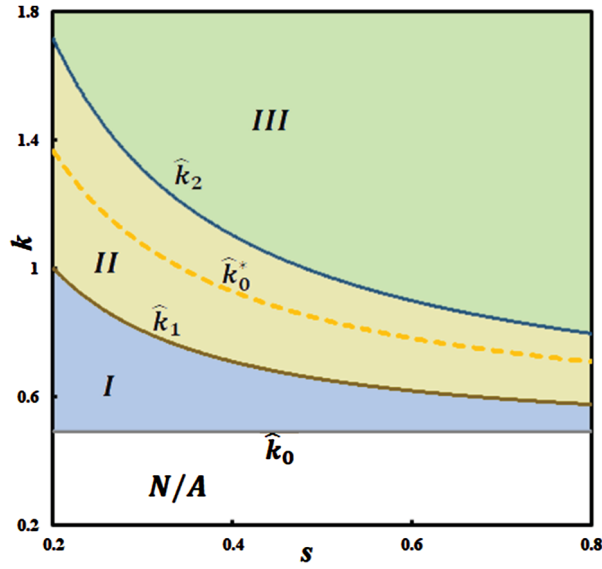


Figure 5. The strategic preferences in the absence of PL products ($c_R = 0.8, b = 0.5$).

AI technology (s_A) affordably, enhancing consumer purchase intent and reducing the retailer's operational service costs. Consequently, the platform raises commission fees, increasing its profits, while the retailer benefits from cost savings and higher sales, leading to mutual profitability. As AI R&D costs increase, an inverse relationship is observed compared to the baseline model (Figure 5, Region II). Here, the retailer's profit continues to grow, but the platform reduces the agency fee (f) to maintain cooperation with the retailer, rendering the profit from fees insufficient to cover the AI R&D costs it bears. Despite declining demand and prices, cost savings and lower commissions sustain the retailer's profitability. With high AI R&D costs (Figure 5, Region III), limited AI investment diminishes NB product demand and service efficiency, resulting in profit losses for both parties. Furthermore, the platform can profit from adopting AI technology only if the AI service level surpasses the traditional operational service level ($k < \hat{k}_0^*$, where $\hat{k}_1 < \hat{k}_0^* < \hat{k}_2$). Nonetheless, if the AI service level is too high, it may actually erode the platform's profit within the range $\hat{k}_1 < k < \hat{k}_0^*$.

6.3. AI technology fully covers traditional operational service costs

This section explores a scenario where AI technology completely replaces traditional manual services, thus eliminating conventional operational service costs for both the platform and the retailer. In this model, adopting AI technology can reduce the operational service cost to zero. Consequently, the platform bears the sole

responsibility for AI development costs, while traditional operational service costs, c_E and c_R , are eliminated. This setting gives rise to three distinct scenarios: the platform adopts AI technology (Model RNA), adopts but does not share AI technology (Model RPA), and adopts and shares AI technology (Model RDA). The profit functions for these models are:

$$\pi_E^{RNA} = f q_R + (p_E - c_E) q_E,$$

$$\pi_R^{RNA} = (p_R - f - c_R) q_R$$

$$\pi_E^{RPA} = f q_R + p_E q_E - \frac{k s_A^2}{2},$$

$$\pi_R^{RPA} = (p_R - f - c_R) q_R$$

$$\pi_E^{RDA} = f q_R + p_E q_E - \frac{k s_A^2}{2},$$

$$\pi_R^{RDA} = (p_R - f) q_R$$

Conducting a comparative analysis of these scenarios leads to the following propositions.

Proposition 6.3: *If AI technology reduces operational service cost to zero:*

- (1) *When platform adopts AI technology but does not share it:*
 - (i) *The platform benefits from adopting AI technology only if the AI R&D cost coefficient is low ($k < \hat{k}_3$).*
 - (ii) *The retailer benefits from AI technology adoption only if the AI R&D cost coefficient is high ($k > \hat{k}_4$, where $\hat{k}_4 > \hat{k}_3$).*
- (2) *When platform shares AI technology:*
 - (iii) *If traditional operational service levels are low ($s < c_R$), AI sharing consistently results in a win-win situation for both firms. (iv) If traditional operational service levels are high ($s > c_R$), the platform benefits from AI sharing only when AI R&D costs are low ($k < \hat{k}_5$); the retailer benefits from AI sharing only when AI R&D costs are low ($k < \hat{k}_6$).*

Proposition 6.3 (1) suggests that even when AI eliminates traditional operational service costs, the profit dynamics for supply chain members are similar to those in the baseline model. AI technology introduces a 'Negative Synergy,' where both retailer and platform may incur profit losses within certain cost ranges (Figure 6(a) Region II). If AI R&D costs are high ($k > \hat{k}_4$), the platform must reduce the agency fee f to sustain cooperation, which enhances retailer profitability (Figure 6(a) Region III). Conversely, with low AI R&D costs ($k < \hat{k}_3$),

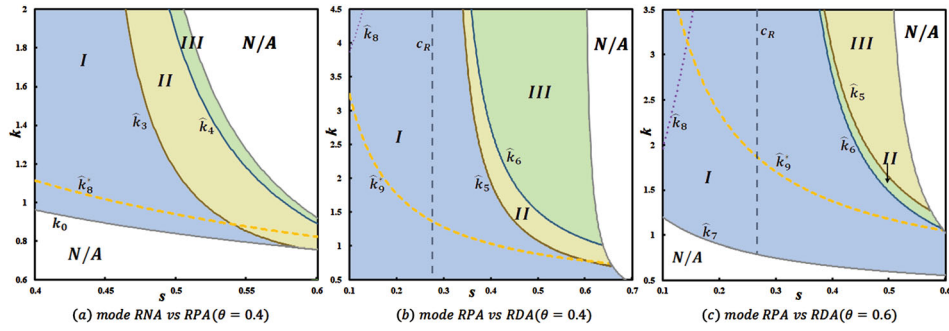


Figure 6. The strategic preferences between model RNA and model RPA ($c_R = 0.3$).

the platform capitalises on technological advantages to achieve profit gains (Figure 6(a) Region I).

Proposition 6.3 (2) highlights differences from the baseline model. In the baseline model, even with AI adoption, both retailer and platform incur some operational service costs. With low traditional operational service levels, AI not only boosts consumer purchase intention but also eliminates cost pressures entirely, leading to a natural win-win situation without complex trade-offs between consumer preference θ and the AI R&D cost coefficient k . When traditional operational service levels are substantial, the profit dynamics for the retailer and the platform closely align with those in the baseline model. Specifically, when AI R&D costs are low, both the platform and the retailer benefit, resulting in a win-win outcome (Region I in Figure 6). Conversely, high AI R&D costs burdening both parties, leading to profit losses. A key distinction from the baseline model is observed: when consumer preference for PL products is low (Region II in Figure 6(b)), there exists an intermediate AI R&D cost range where the retailer benefits while the platform incurs losses. Conversely, when consumer preference for PL products is high (Region II in Figure 6(c)), an intermediate AI R&D cost range benefits the platform while reducing the retailer's profit.

This distinction arises because, with low θ , PL products become less competitive, requiring the platform to enhance competitiveness by relying on high AI service levels. The lower θ also reduces PL demand sensitivity to s_A , indicating the platform can only profit from AI technology under relatively low cost pressures ($k < \hat{k}_5$). In this scenario, the retailer's product remains more competitive, and AI adoption, which eliminates traditional operational service costs, allows the retailer to enjoy a larger profit margin compared to the platform. On the other hand, with high θ , PL products are more competitive. This allows the platform to cover AI R&D costs and achieve higher profits by eliminating traditional operational expenses, even with relatively high AI R&D costs, and increasing PL demand. In this case,

the retailer's NB product becomes less competitive, and the cost savings fail to offset the losses from decreased demand, which ultimately reduces profit. These findings suggest that when AI technology only partially replaces traditional operational service costs, it serves as a bargaining chip in competitive dynamics, and a win-win outcome depends on both cost savings and demand synergy. However, when AI fully replaces traditional operational costs, it reshapes the supply chain's competitive landscape, with product competitiveness becoming the primary driver of profit distribution. This amplifies the impact of θ on supply chain power distribution, requiring the platform to tailor its AI investment and ecosystem coordination strategies based on its market position.

In this model, unlike the baseline model, a decline in total market demand occurs only when the AI R&D cost coefficient is relatively high ($k > \hat{k}_8$). This divergence arises because, in the baseline model, lower AI R&D costs improve service levels and reduce operational expenses. However, the resulting increase in prices and agency fees limits market expansion, creating a paradox in which revenue rises while market size contracts. However, when AI fully replaces traditional operational service costs, sufficiently low AI R&D costs allow both the platform and the retailer to eliminate traditional service expenses. This provides greater flexibility in managing pricing strategies and stimulating demand growth. Conversely, high AI R&D costs result in insufficient investment in AI, leading to a dual decline in service quality and consumer utility. The modest reduction in price fails to activate the market, ultimately contracting total demand. Furthermore, we analyze how changes in AI service levels affect the profitability of supply chain members. Unlike in the benchmark model, when the platform adopts AI technology, any enhancement in service levels through AI consistently increases platform profits ($k < \hat{k}_8^*$). Even if AI adoption leads to reduced service levels ($k > \hat{k}_8^*$), the platform can still benefit from cost savings, as AI serves as a complete substitute for traditional services. When the platform shares AI technology, these

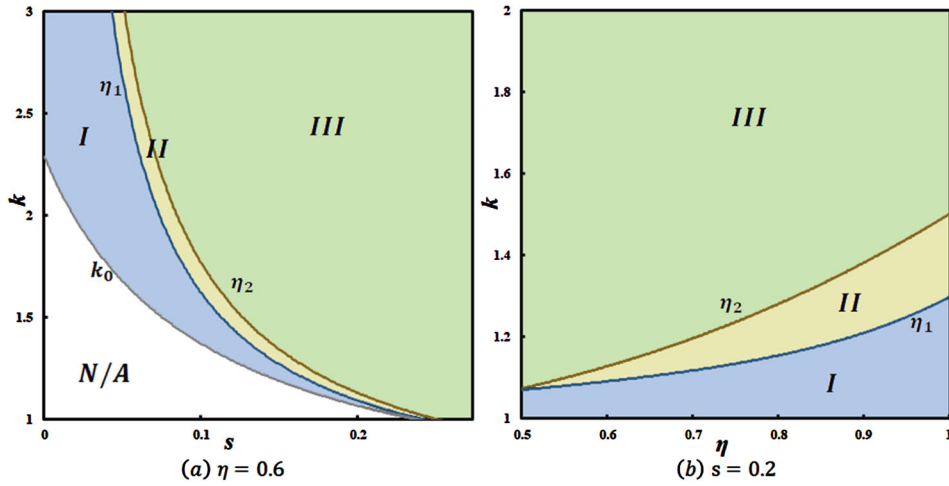


Figure 7. The strategic preferences after platform partially shares AI services ($c_R = 0.3, \theta = 0.7, \beta = 0.1$).

cost-saving advantages can also yield positive outcomes for supply chain members, even with reduced service levels. However, when traditional service levels are high, sharing AI technology may become unprofitable due to increased R&D costs (Figure 6(b), $k < \hat{k}_9^*$). These results further validate our conclusion in Proposition 5.2.

6.4. Platform provides incomplete AI technology to retailer

In this section, we study the scenario where the e-commerce platform might provide only partial AI service technology to the retailer to protect the competitiveness of its PL brand. We introduce a parameter η , where $\eta \in (0.5, 1)$ represents the proportion of AI services that the platform shares with the retailer. Consequently, when the platform shares AI technology with the retailer, consumer utility for NB and PL products can be expressed as $U_R = v - p_R + \eta s_A$ and $U_E = \theta(v + s_A) - p_E$, respectively. The corresponding demand functions for NB and PL products are: $q_R = 1 - \frac{p_R - p_E + \theta s_A - \eta s_A}{1 - \theta}$ and $q_E = \frac{p_R - p_E + \theta s_A - \eta s_A}{1 - \theta} - \frac{p_E - \theta s_A}{\theta}$. In this section, we compare two scenarios: (i) the platform adopting AI technology without sharing it (Model PA) and (ii) the platform sharing partial AI technology (Model PDA). The profit function under the PDA scenario is presented as follows.

$$\begin{aligned}\pi_E^{PDA} &= f q_R + [p_E - (c_E - \beta s_A)] q_E - \frac{k s_A^2}{2} \\ \pi_R^{PDA} &= (p_R - f - (c_R - \beta \eta s_A)) q_R\end{aligned}$$

Due to the computational complexity, we utilise numerical simulations to support the profit comparison results, as shown in Figure 7.

Observation 6.1: When the platform partially shares AI services with the retailer: (1) Sharing AI technology results in a win-win outcome for both the platform and the retailer only when the shared AI service level is high ($\eta > \eta_1$). (2) At a moderate level of shared AI technology ($\eta_2 < \eta < \eta_1$), the platform benefits from sharing, but the retailer's profit is adversely affected. (3) At a low level of shared AI technology ($\eta < \eta_2$), both the platform and the retailer experience profit losses.

Figure 7(a) demonstrates that when the platform shares only part of its AI technology, the profit variation pattern among supply chain members remains largely consistent with the scenario in the baseline model of full AI-sharing. This suggests the platform primarily allocates technological gains by adjusting the agency fee f and AI service level s_A . Despite changes in the AI-sharing proportion η , profit distribution remains consistent with the baseline model. Figure 7(b) reveals that in Region I, where the platform shares a higher proportion of AI technology, with enhanced AI capabilities, the retailer can reduce costs and boost product competitiveness, thereby increasing profits. Concurrently, the platform can impose higher agency fees, enhancing its profits leading to a win-win situation. However, in Region II, as the AI-sharing coefficient η decreases, the platform strategically limits AI sharing to bolster the competitiveness of its PL products. Here, the platform gains higher profits through the PL channel, while the retailer restricted by limited AI access, achieve minimal cost savings and face increased agency fees, resulting in reduced profits. This reflects strategic exploitation under partial AI sharing. In Region III, with very low AI sharing, the platform cannot justify higher agency fees. The retailer lowers NB product prices to remain competitive, which forces the

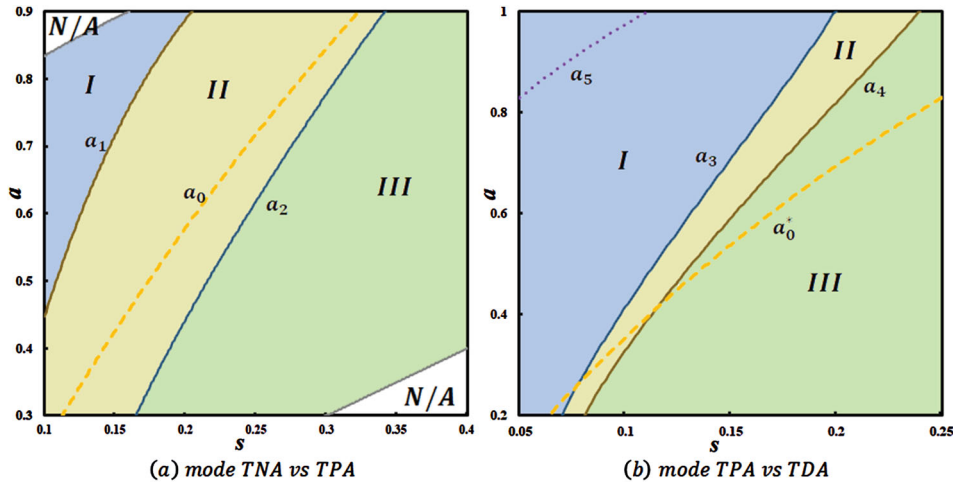


Figure 8. The strategic preferences under some consumers prefer traditional human-operated services ($c_R = 0.3, c_E = 0.5, \theta = 0.7, \beta = 0.1$).

platform to reduce PL prices under competitive pressure. Consequently, the platform's revenues from PL sales and agency fees fall short of covering costs, leading to decreased profits. These findings underscore a crucial insight: restricting AI access to strengthen PL competitiveness doesn't necessarily benefit the platform. The essence of an AI-sharing strategy is to balance value creation and distribution. The platform must carefully strategise AI deployment to ensure technological collaboration fosters mutual profitability.

6.5. Some consumer preference for human services

In practice, not all consumers favour AI-enabled operational services. Some even exhibit aversion to AI and instead prefer traditional human-operated services (Ding et al. 2025). Prior research confirms that algorithm aversion can cause certain consumer groups to avoid AI services (Bockstedt and Buckman 2025). In practice, platforms like Amazon and Alibaba adopt a service model where consumers initially interact with AI, while human and traditional operations remain in the background. This 'AI front-end with human back-up' approach allows users to fall back on traditional human services if they are dissatisfied with the AI service.¹⁵ Therefore, we categorise consumers into two groups: those who prefer AI services and those who prefer human services. Let α denote the proportion of AI-inclined consumers. When the platform adopts AI technology, AI-inclined consumers perceive the AI service level s_A . On the other hand, human-inclined consumers, despite initially being exposed to AI services, prefer human interaction and thus perceive the traditional service level s . If the platform adopts AI technology only for PLs, the utilities for AI-inclined consumers purchasing NB and PL

products are: $U_R^A = v + s - p_R$ and $U_E^A = \theta(v + s_A) - p_E$. The utilities for human-inclined consumers purchasing NB and PL products are: $U_R^A = v + s - p_R$ and $U_E^A = \theta(v + s) - p_E$. The corresponding demands are: $q_R = \alpha \left(1 - \frac{p_R - p_E + \theta s_A - s}{1 - \theta} \right) + (1 - \alpha) \left(1 - \frac{p_R - p_E + \theta s - s}{1 - \theta} \right)$, $q_E = \alpha \left(\frac{p_R - p_E + \theta s_A - s}{1 - \theta} - \frac{p_E - \theta s_A}{\theta} \right) + (1 - \alpha) \left(\frac{p_R - p_E + \theta s - s}{1 - \theta} - \frac{p_E - \theta s}{\theta} \right)$. When the platform shares AI technology with the retailer, the utilities for AI-inclined consumers purchasing NB and PL products are: $U_R^A = v + s_A - p_R$ and $U_E^A = \theta(v + s_A) - p_E$. Similarly, the utilities of human-inclined consumers for purchasing NB and PL products are: $U_R^A = v + s - p_R$ and $U_E^A = \theta(v + s) - p_E$. At this point, the demands for NB and PL products are: $q_R = \alpha \left(1 - \frac{p_R - p_E + \theta s_A - s_A}{1 - \theta} \right) + (1 - \alpha) \left(1 - \frac{p_R - p_E + \theta s - s}{1 - \theta} \right)$, $q_E = \alpha \left(\frac{p_R - p_E + \theta s_A - s_A}{1 - \theta} - \frac{p_E - \theta s_A}{\theta} \right) + (1 - \alpha) \left(\frac{p_R - p_E + \theta s - s}{1 - \theta} - \frac{p_E - \theta s}{\theta} \right)$. Given the analytical complexity, we rely on numerical simulations to compare profits, as illustrated in Figure 8.

Observation 6.2: When some consumer preferences lean towards human services: (1) If the platform adopts but does not share AI technology, it can generate profits only when the proportion of AI-inclined consumers is sufficiently high ($a > a_1$). In contrast, the retailer can profit only when this proportion is relatively low ($a < a_2$). (2) If the platform shares AI technology, he can profit only when the proportion of AI-inclined consumers is high ($a > a_4$), while the retailer can profit only if the proportion is also high ($a > a_3$).

Figure 8(a) depicts the supply chain under platform adoption without sharing. Profits improve only when the

share of AI-inclined consumers is high (Region I), as AI adoption enhances demand and boosts the platform's revenue. When the proportion of AI-inclined consumers is moderate (Region II), the 'Negative Synergy' highlighted in the baseline model persists, producing a lose-lose outcome for both parties. When the proportion is low (Region III), AI adoption provides little benefit, PL's competitiveness remains weak, and the retailer indirectly gains profits. Importantly, the platform can profit from AI only if its AI service level surpasses the traditional service level. However, a higher AI service level may also incur extra costs and reduce demand, thereby eroding the platform's profit in certain cases (when $a_0 < a < a_1$). Figure 8(b) shows the scenario when the platform shares its AI technology. With a high proportion of AI-inclined consumers (Region I), sharing strengthens the competitiveness of both NB and PL products, yielding a win-win outcome for both parties. When the proportion of AI-inclined consumers is moderate (Region II), the platform still benefits from dual income streams (PL sales and agency fees) while the retailer suffers from diminished competitiveness. With a low proportion of AI-inclined consumers (Region III), both parties incur losses. Furthermore, even when the AI service levels outperform the traditional service levels (when $a > a_0^*$), high traditional service levels may still lead to mutual losses. Conversely, when AI service levels underperform (when $a < a_0^*$), if traditional service levels are low, sharing AI technology can still lead to a win-win situation for both parties.

7. Conclusion

7.1. Concluding remarks

With the expansion of the online retail market and intensifying brand competition, platforms and retailers face rising operational service costs. AI technology emerges as a promising solution to enhance consumer shopping experiences and reduce operational expenses. Platforms such as JD and Amazon offer AI tools that help retailers enhance their services. However, platforms must carefully weigh the substantial R&D costs of AI adoption against competitive pressures. This study develops a two-stage supply chain model involving a platform and a retailer, each selling their products in the market. The platform decides whether to adopt and share AI technology to enhance its operations and reduce operational service costs. In the baseline model, we assess conditions under which the platform implements or shares AI technology with the retailer. The extended analysis explores additional factors and examines how the platform's AI-related decisions evolve under various scenarios.

We find that when the AI R&D cost coefficient is low, the platform adopts AI, which enhances the competitiveness of its PL products. This allows product prices and agency fees to increase, boosting the platform's profit while reducing the retailer's profit. The retailer benefits only when AI R&D costs compel the platform to reduce agency fees, thereby allowing demand to flow back. Interestingly, moderate AI R&D cost coefficients lead to losses for both parties; the platform's marginal returns from technological investments fail to cover costs, while the retailer cannot benefit due to the competition's *Negative Synergy*. Furthermore, low AI R&D cost coefficient and technology sharing weaken the competitiveness of PLs, reducing PLs' market share and total demand. However, AI-enabled cost savings and improved consumer experiences can still yield a win-win outcome. High AI R&D cost coefficient, despite expanding market demand, results in profit losses due to diminishing returns. A strong consumer preference for PL products narrows the benefits of AI sharing, suggesting that excessive product homogenisation harms supply chain members.

When the platform adopts AI technology, profitability is achievable only if the AI service level significantly surpasses that of traditional operational services. In the context of sharing AI technology, if consumer trust in PL products is low, supply chain members can profit only when the AI service level is much higher than the traditional operational services. Otherwise, platform revenues may not cover R&D costs. Conversely, with high PL trust, even reduced service levels can lead to mutually beneficial outcomes through substantial cost savings. However, excessively pursuing high AI service levels might erode profits due to increasing R&D expenses. Moreover, variations in consumer perceptions and the differential effects of AI can further alter the relationship between service-level changes and the profitability of supply chain members.

Changes in consumer preferences do not influence AI investment decisions. In a PL-advantaged market, AI sharing reduces demand only when costs are high; otherwise, it expands the market. In an NB-dominated market, AI technology sharing may trigger market contraction at lower technological cost thresholds due to increased competition. This shows that AI sharing by leading brands is more inclusive and resilient to fluctuations of secondary brands. When PL products are overshadowed by NB products, the AI-driven value distribution logic remains unchanged. However, reliance on retailer fees may create a 'free-riding' effect, eroding the platform's profit. Furthermore, when AI fully replaces traditional services, AI sharing enables unconditional win-win outcomes at lower service levels. However, intensified competition introduces complex dynamics. Sharing

incomplete AI to maintain the competitiveness of PL products may not benefit the platform. The core of AI-sharing strategies lies in balancing value creation and distribution, rather than in the mere forms of AI sharing.

7.2. Managerial implications

Our research provides valuable insights for platforms as they navigate AI strategy selection, emphasising several key aspects.

First, lower AI R&D costs enable platforms to substantially enhance the competitiveness of PL products and improve profitability, though careful calibration of pricing and commission strategies is required to avoid crowding out retailers. In contrast, moderate R&D costs may result in a lose-lose outcome, as the marginal returns of technology fail to offset the expenses. Platforms can mitigate this ‘Negative Synergy’ through cost-sharing mechanisms. For example, Amazon’s traffic subsidies and SaaS-based subscriptions transform AI investments into joint benefits rather than unilateral burdens.

Second, when sharing AI technology, platforms should substantially raise service levels under low PL trust; otherwise, revenues may be insufficient to cover costs. However, under high PL trust, even lowering service levels can remain profitable. Interestingly, enhancing service levels through AI may actually reduce platform profits, as demonstrated by Y. Wang et al. (2025), who showed that when back-end efficiency is already high, the optimal strategy may be to avoid AI adoption altogether to prevent unnecessary expenditures. Therefore, platforms should calibrate AI service levels in line with consumer trust in PL products rather than indiscriminately pursuing technological upgrades.

Last, in practice, JD.com has demonstrated this principle by reducing retailers’ operating costs by 50% through its ‘AI All-in-One Service Package,’ thereby expanding the overall platform market. Nevertheless, sharing AI in markets where PL already holds a strong advantage may erode PL’s distinctiveness. Hence, platforms may adopt context-specific AI strategies, such as promoting AI openness and sharing in weak-PL markets, while refraining from or partially sharing AI technology in strong-PL markets to balance scale expansion with differentiated competition.

7.3. Limitations and future studies

This study has limitations and suggests directions for future research. We assume identical traditional service levels for simplicity, although they may vary due to individual decisions. Future research could treat traditional service levels as decision variables. For the sake

of simplification, we assume zero marginal costs for both PL and NB products. However, in reality, differentiated production costs are often a critical determinant of firms’ strategic choices. Therefore, future research could explore how variations in cost structures affect product competition and technology sharing. Furthermore, the AI sharing decisions may be influenced by additional factors such as brand spillover effects or consumer aversion to AI. Future research could explore these dimensions in greater depth. Finally, the impact of AI may extend to future sales trends. Future studies could explore AI applications in broader contexts to comprehensively understand market dynamics.

Notes

1. <https://www.statista.com/outlook/emo/ecommerce/worldwide>
2. <https://xueqiu.com/3689359053/153075866>
3. <http://capital.people.com.cn/n1/2020/0811/c405954-31817817.html>
4. <https://zhuanlan.zhihu.com/p/686026791>
5. https://www.sohu.com/a/763670223_745455
6. <https://new.qq.com/rain/a/20230525A0AFYH00>
7. <https://caijing.chinadaily.com.cn/a/202309/18/WS6507fc29a310936092f22471.html>
8. <https://zhuanlan.zhihu.com/p/686601699>
9. <https://www.reuters.com/business/shopify-launches>
10. <https://www.businessinsider.com/amazon>
11. <https://www.sohu.com/a/huawei>
12. <https://www.jiemian.com/article/9807330.html>
13. <https://www.softwareadvice.com>
14. <https://nypost.com>
15. <https://d3.harvard.edu>

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Data availability statement

Data sharing is not applicable to this article as no new data were created or analysed in this study.

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