The Impact of AI Adoption on Competition and Social Welfare in Green Supply Chains

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Abstract. Under the background of current digital and intellectual transformation, artificial intelligence (AI) is profoundly changing the operational and competitive mechanisms of supply chains. This study focuses supply chains involving a single manufacturer and a retailer. The main context explores the impact of AI on green supply chain decision-making strategies and profits distribution. By developing an analytical model, this paper discusses how AI adoption reshapes pricing, green investment and profit distribution between manufacturers and retailers by eliminating the demand forecasting bias (λ). The result has found a 'dual effect' of AI; while the overall efficiency of the supply chain leads to opposing changes in profits between two parties. This situation creates an 'AI paradox' which means that the actual effect is affected by key parameters such as the initial market forecasting deviation, the intensity of consumers' green preferences, and the cost of green input. The outcomes reveal that enterprises need to promote AI with collaborative mechanisms to coordinate conflicts of interest and achieve sustainable growth.

Keywords: Artificial Intelligence, Green Supply Chain, Game Theory, Profit Distribution, Demand Forecasting

1 Introduction

The ongoing trends of digitisation and intelligentisation have positioned Artificial Intelligence (AI) as a vital competitive tool for enterprises. By enhancing demand forecasting, optimising inventory management, streamlining transportation routes, AI improves efficiency and reduces costs in supply chain operations. Simultaneously, AI supports the transition towards green production and low-carbon transformation. Real-world cases illustrate this trend. Tesla uses AI to optimise its battery raw material supply chain, reducing resource waste. IKEA employs AI to forecast optimal logistics routes, cutting transportation emissions. These examples demonstrate how AI can simultaneously enhance economic efficiency and environmental sustainability.

This study aims to fill that gap by addressing three core questions:

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- How does AI adoption influence the pricing strategies and green investment decisions, when manufacturers and retailers adopt AI respectively?
- Does AI adoption lead to the reallocation of profits among participants in the supply chain? What are the outcomes?
- How do the other critical parameters, such as deviation in market demand forecast and green input cost, influence the final effect of AI adoption?

To answer these questions, this study develops green supply chain models and discuss several critical parameters' impacts on pricing strategies and general profits. The outcomes illustrate that AI adoption can reshape the pricing and green investment strategies by revising the demand forecast. Simultaneously, it leads to profits reallocation between manufacturers and retailers. The profits of both sides mostly show a trend of opposing changes. These outcomes are influenced by the demand forecast deviation, green preference, and cost parameters. To resolve the conflicts of interest and achieve the valuable green transformation, all participants within a green supply chain need to promote AI adoption with collaborative mechanisms.

Following content of this study mainly includes three parts. The second part reviews critical literature about AI adoption, and green supply chain management. The third part develops theoretical models and analyses outcomes. Then, the final part conducts sensitivity analysis and discusses research conclusions and management insights.

2 Literature Review

2.1 AI Adoption in Supply Chains

AI integration in manufacturing and supply chain processes has become increasingly widespread. While studies have shown that AI improves forecasting, inventory management and decision efficiency in supply chain operations, its integration with green supply chains remains underexplored (Carbonneau et al., 2008[4]; Sharma et al., 2022[15]; Bala, P. K., 2010[1]). Büchi et al. (2022)[3] highlight that AI not only enhances operational efficiency but also serves as a catalyst for digital transformation. Nevertheless, the adoption of AI continues to face obstacles such as high upfront investment and organisational resistance to change (Müller et al., 2021[14]; Wamba et al., 2024[7]). Furthermore, the realisation of AI's benefits heavily depends on the quality of a company's data infrastructure and its pool of skilled personnel (Li et al., 2023[13]). The effect of AI on enhancing the total factor productivity of enterprises still varies significantly across different industries and specific application scenarios (Zhao et al., 2014[21]; Büchi et al., 2022[3]). Moreover, AI technology can enhance the volatility of supply chains and effectively support decision-making in crises (Ivanov, 2022[11]). Generally, AI technology has significant potential, but the actual impacts depend on industries and scenarios (Wamba et al., 2022[8]).

2.2 AI Integration and Governance in Green Supply Chains

Research on green supply chains focuses on aligning economic and environmental responsibility. With rising consumer environmental awareness, significant research has examined the mechanisms of supply chain coordination through green production, pricing strategies, and game theory analysis under competitive supply chain structures (Heydari et al., 2020[10]; Xin et al., 2020[19]; Taleizadeh et al., 2016[17]). Some other researches have shown that AI can improve the sustainability and resilience of green supply chains (Gupta et al., 2023[9]). Simultaneously, AI technology can help enterprises cope with pressure from demand uncertainty and environmental protection regulations, enabling collaboration can be achieved in a closed-loop green supply chain (Kumar et al., 2022[12]; Chen & Li, 2021[5]). However, the intervention of AI can also create a 'green appearance' without truly internalising the environmental and social costs (Dauvergne, 2022[6]). Therefore, scholars have emphasized the necessity of placing AI under an effective governance mechanism and focusing on multiple impacts of AI on net profit, environmental impact and social welfare in the supply chain (Bejlegaard et al., 2021[2]; Zhang et al., 2021[20]). Policies, such as carbon taxes, can enhance social welfare level by influencing pricing decisions in the supply chain (Zhou et al., 2018[22]). These discussions have revealed that the practice of green supply chains is shifting from the traditional trade-off to an integrated optimisation stage that combines AI technology and sustainable governance (Sombultawee & Boonprakob, 2019[16]; Wang et al., 2019[18]).

3 Model Description

This study focuses on the dual green supply chains which are formed by the single manufacturer and the single retailer. The market baseline demand is represented by a ; b represents the intensity of consumer green preference. The green investment cost function is $cg+kg^2/2$ with increasing marginal cost, while k is the marginal cost coefficient of green input. Manufacturer first decides the product green level g ($g\geq 0$), then confirms the wholesale price w ($w>c$), and c is the unit production cost. Subsequently, retailer decides on the market retail price p, the market demand is q. The key parameters and decision variables used in the model are summarized in Table 1.

When the AI technology is not adopted, the retailer has a cognitive bias of the potential market size, so the market demand function is $q=\lambda a-p+bg$, while λ is the demand forecast parameter ($\lambda\neq 1$ represents forecast deviation). After adopting AI technology, the forecast deviation is eliminated, so the demand function is $q=\mu a-p+bg$, while λ is the market accuracy coefficient with AI (λ is standardized as 1). This study uses manufacturer profits (π_M), retailer profits (π_R) as assessment criteria.

Table 1. Parameter and Symbol Description

Symbol	Meaning and Description
a	Market baseline demand (Consumers' basic preference for green products)
b	Intensity of consumer green preference
g	Product green level
c	Unit green investment cost
k	Marginal cost coefficient for green investment
q	Market demand
p	Retail price (set by the retailer)
w	Wholesale price (set by the manufacturer)
π_M	Manufacturer profit
π_R	Retailer profit
λ	Retailer's estimated coefficient for potential demand (without AI)
μ	Retailer's market accuracy coefficient with AI (Usually, standardised as 1)

3.1 Model without AI Technology

When AI is not adopted, the market demand is

$$q=\lambda a-p+bg \tag{1}$$

The manufacturer profit function is

$$\pi_M=(w-c)q-kg2 \tag{2}$$

While, the retailer profit function is

$$\pi_R=(p-w)q \tag{3}$$

Retail price set by the retailer is

$$p=(\lambda a+bg+w)/2 \tag{4}$$

Manufacturer's expected profit function is

$$\pi_M=(w-c)(\lambda a+bg-w)/2-kg^2 \tag{5}$$

Property 1. In the model without AI technology, the manufacturer's optimal product greenness level and optimal wholesale price are:

$$g^*=(\lambda ab-cb)/(8k-b^2) \tag{6}$$

$$w^*=[8k(\lambda a+c)-2b^2c]/2(8k-b^2)= [4k\lambda a+c(4k-b^2)]/(8k-b^2) \quad (7)$$

Both g^* and w^* are jointly influenced by λa, c, b, and k. When the value of b rises, g^* also increases, but the value of w^* is lower; an increase in k suppresses g^* and raises w^*; the market size expansion positively influences g^* and w^*. At the same time, an increase in c suppresses g^* and raises w^*. With the value of g^* and w^*., the retailer can set final retail prices.

Property 2. In the model without AI technology, the optimal retail price is

$$p^*=(\lambda a+bg+w)/2 \quad (8)$$

Substitute equation (6) into equation (8), then

$$p^*=[2k(3\lambda a+c)-b^2c]/(8k-b^2)=[6k\lambda a+c(2k-b^2)]/(8k-b^2) \quad (9)$$

Property 2 reveals that p^* is positively related to λa, g^*, and w^*. The retailer's pricing strategy reflects the issue of marginalization.

Property 3. With the optimal solutions of g^*, w^*, and p^*, the optimal level of manufacturer profits is

$$\pi_M^*=(w-c)q-kg^2=k(\lambda a-c)^2/(8k-b^2) \quad (10)$$

π_M^* depends on the balance among market size, cost variance, and green investment cost. The optimal level of retailer profits is

$$\pi_R^*=(q^*)^2=4k^2(\lambda a-c)^2/(8k-b^2) \quad (11)$$

These three properties conclude the decision-making and profit distribution mechanism under the model without AI.

3.2 Model with AI technology

Under the model with AI technology, demand forecast is accurate (μ=1), so the demand function is

$$q=\mu a-p+bg \quad (12)$$

Property 4. After adopting the AI technology, the optimal levels of green level and wholesale price are

$$g_{AI}^*=(ab-cb)/(8k-b^2) \quad (13)$$

$$w_{AI}^*=[8k(a+c)-2b^2c]/2(8k-b^2)= [4ka+c(4k-b^2)]/(8k-b^2) \quad (14)$$

AI technology can improve the efficiency through eliminating the forecast deviation. The increase in value b leads to a growth in g_{AI}^* and a decrease in $\mathbf{w_{AI}}^*$. On the contrary, an increase in value k suppresses g_{AI}^* and raises w_{AI}^*.

The retailer as a follower sets the optimal retail price p_{AI}^* based on g_{AI}^* and w_{AI}^*:

$$p_{AI}^*=(a+bg+w)/2 \quad (15)$$

Substitute function (14) into (15), the next property can be obtained.

Property 5. After adopting the AI technology, the optimal retailing price is:

$$p_{AI}^{*}=[2k(3a+c)-b^{2}c]/(8k-b^{2})=[6ka+c(2k-b^{2})]/(8k-b^{2}) \tag{16}$$

AI facilitate the pricing strategy by using accurate market demand data. The results reflect the actual costs and market affordability. It helps reduce the distortion caused by 'double marginalization' and improve the supply chain efficiency.

Property 6. With the AI technology, manufacturer's optimal profit is:

$$\pi_{MAI}^{*}=(w-c)q-kg^{2}=k(a-c)^{2}/(8k-b^{2}) \tag{17}$$

And the retailer's optimal profit is:

$$\pi_{RAI}^{*}=4k^{2}(a-c)^{2}/(8k-b^{2}) \tag{18}$$

By improving demand forecasting accuracy, AI adoption helps both sides align the product green level with market demand and optimize investment and sales. When the retailer's profit grows faster than the manufacturers and the value k is high, AI has more prominent impacts on enhancing efficiency.

3.3 Impact of AI Technology

By comparing the optimal solutions with AI and without AI, it is obvious that AI can reshape the supply chain decisions by eliminating the demand forecasting deviation ($\lambda \neq 1$). Its impact exhibits a dual effect. On one side, AI promotes the product green level and wholesale price which drives a supply-side improvement. In addition, AI also raises the retail price. On the other side, the profit changes of both parties can be contrary, forming an 'AI paradox' where the efficiency enhancement and profits create conflicts of interest. The following section will discuss the results of comparison in detail.

Conclusion 1. Net change of the optimal wholesale due to AI is:

$$\Delta w^{*}=w_{AI}^{*}-w^{*}=[4ka+c-(4k-b^{2})]/(8k-b^{2})-(\lambda ab-cb)/(8k-b^{2})= (1-\lambda)ab/(8k-b^{2}) \tag{19}$$

Net change of the optimal green level due to AI is:

$$\Delta g^{*}=g_{AI}^{*}-g^{*}=[(ab-cb)/(8k-b^{2})-(\lambda ab-cb)/(8k-b^{2})= (1-\lambda)ab/(8k-b^{2}) \tag{20}$$

1)When the market demand is underestimated ($\lambda<1$), $\Delta w^{*}>0$, $\Delta g^{*}>0$,, so AI raises the wholesale price and product green level.

2)When the market demand is overestimated ($\lambda>1$), $\Delta w^{*}< 0$, $\Delta g^{*}<0$, so AI suppresses the wholesale price and product green level.

Conclusion 2. Net change of the optimal retail price is:

$$\Delta p^{*}=p_{AI}^{*}-p^{*}=6k(1-\lambda)a/(8k-b^{2}) \tag{21}$$

1) When the market demand is underestimated ($\lambda<1$), $\Delta p^{*}>0$, which means AI raises the retail price.

2) When the market demand is overestimated ($\lambda>1$), $\Delta g^*<0$, which means AI leads to a lower retail price.

Conclusion 3. Net change of the optimal manufacturer profit is:

$$\Delta\pi_M^*=\pi_{MAI}^*-\pi_M^*=k(a-c)^2/(8k-b^2)-k(\lambda a-c)^2/(8k-b^2)= ka(1-\lambda)[(1+\lambda)a-2c](8k-b^2) \quad (22)$$

1) $\lambda<1$,

When $c<(1+\lambda)a/2$, $\Delta\pi_M^*>0$, AI leads to a higher level of manufacturer profits.

When $c>(1+\lambda)a/2$, $\Delta\pi_M^*<0$, AI causes a drop in manufacturer profits.

2) $\lambda>1$,

When $c<(1+\lambda)a/2$, $\Delta\pi_M^*<0$, AI suppresses the manufacturer profits due to the shrinking market.

When $c>(1+\lambda)a/2$, $\Delta\pi_M^*<0$, AI leads a higher level of manufacturer profits because it avoids over-investment.

Net change of the optimal retail profit is:

$$\Delta\pi_R^*=\pi_{RAI}^*-\pi_R^*=4k^2a(1-\lambda)[(1+\lambda)a-2c]/(8k-b^2)^2 \quad (23)$$

1) When $\lambda<1$, $\Delta\pi_R^*>0$, AI adoption raises the retail profits.

2) When $\lambda>1$, $\Delta\pi_R^*<0$, AI leads to a lower level of retail profits.

This opposition reveals that AI adoption can both improve information efficiency and intensify the conflicts among the supply chain members. The result emphasises on the necessity of designing coordination mechanisms.

4 Sensitivity Analysis

Based on the optimal results, this section will conduct a sensitivity analysis and observe the actual impacts of critical parameters on supply chain decision-making and profit distribution, see figure 1 to 4.

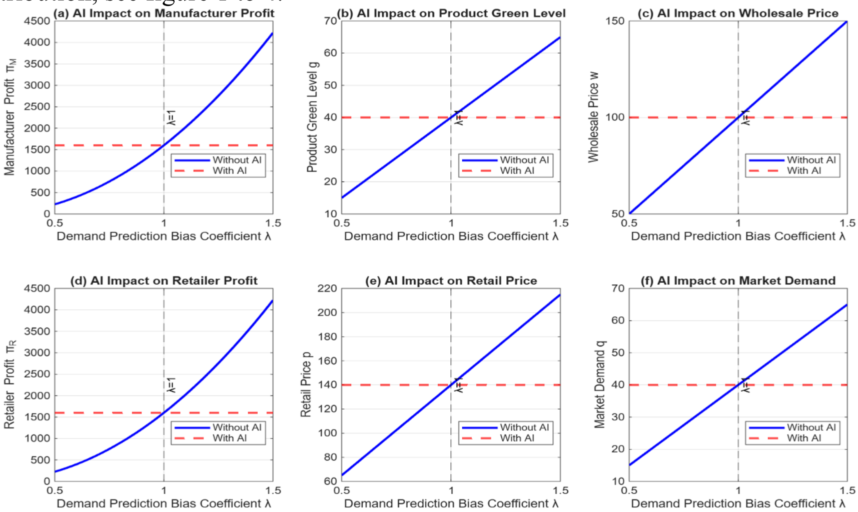

Fig. 1. Senstivity Analysis: Al Impact on Green Supply Chain Decisions and Profits

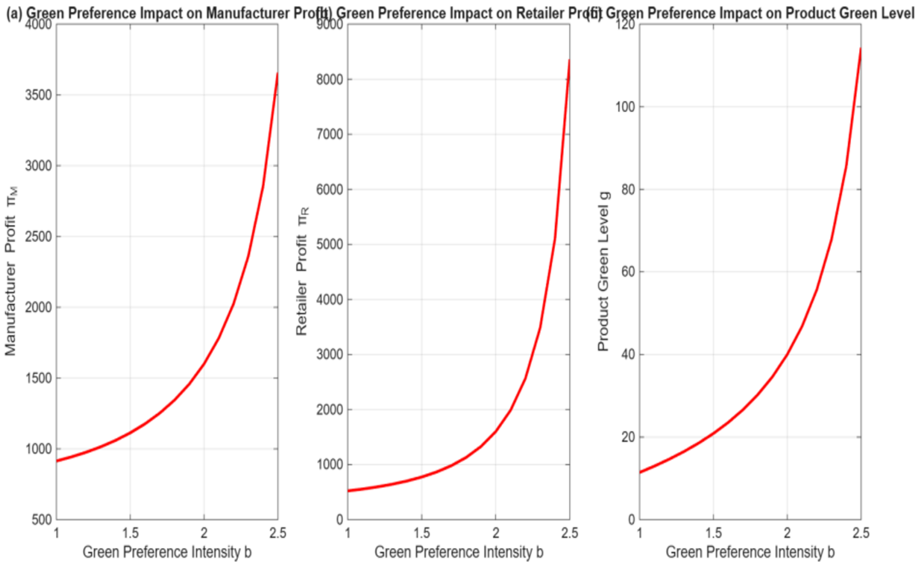

Fig. 2. Impact Analysis of Green Preference intensity on Supply Chain Decisions (With Al)

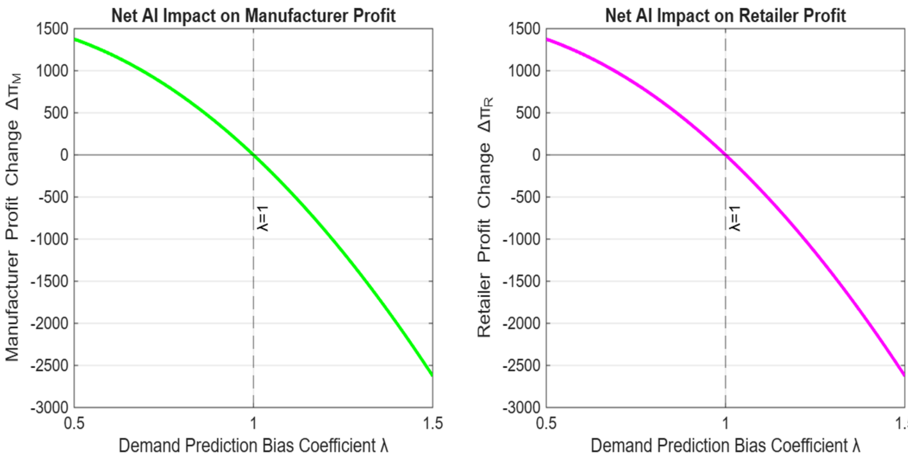

Fig. 3. Net Impact Analysis of AI Technology on Supply Chain Profits

This sensitivity analysis reveals that AI's impact on supply chains highly rely on forecast deviation λ and green preference b. If $\lambda<1$, AI promotes increases in green levels, prices, and market demand, with retailer profits significantly rising, while manufacturer profits are moderated by costs.

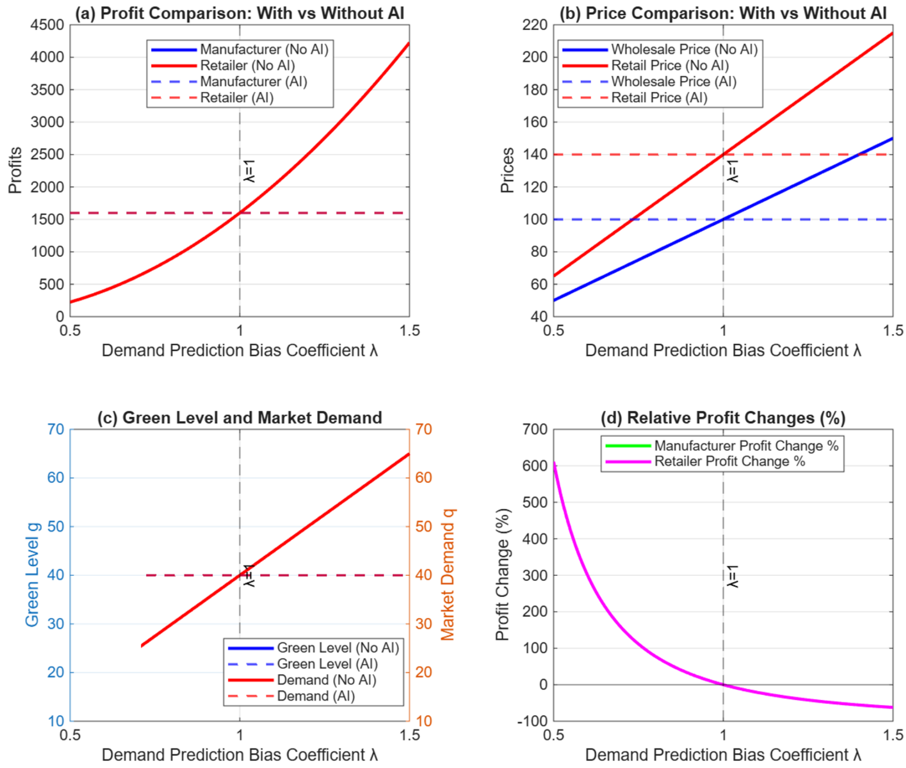

Fig. 4. Comprehensive Analysis of AI lmpact on Green Supply Chain Performance

5 Conclusion

This study shows that AI reshapes green supply chain and profits distribution by eliminating demand forecasting deviation (λ). When λ<1, AI facilitates the green level upgrade and raises price levels, while manufacturers' profits are adjusted by costs. The profit changes of both parties are in opposition, creating an 'AI paradox'. In general, enterprises need to promote AI with a combination of collaborative mechanisms to achieve the optimisation of environmental and economic benefits.

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