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Research article

Closed-loop supply chain decisions for power battery with AI technology under government subsidy

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Abstract: The vigorous development of new energy vehicles has driven an escalating demand for power batteries and a rapidly growing volume of retired batteries. Low recycling efficiency of retired batteries and mismatched cost-benefit allocation of technology investment have emerged as key issues in the closed-loop supply chain. To address these issues, we investigate AI technology investment and contract mechanisms in the closed-loop supply chain of power batteries, taking into account government subsidies. By considering three scenarios, i.e. an independent AI investment model, a cost-sharing model, and a revenue-cost sharing model, we examine how different collaboration mechanisms influence AI investment and collaboration strategies among the participating companies, and also investigate the effects of government subsidies on supply chain decision. Our results show that both coordinated models achieve higher AI investment than the independent model. Additionally, when government subsidies are within a moderate range, both wholesale price and retail price are lowest under the revenue-cost sharing scenario, moderate under the independent investment scenario, and highest under the cost-sharing scenario. Furthermore, supplier profits rise under both coordinated models. Manufacturer profits increase only when the cost-sharing ratio and revenue-sharing ratio are relatively low. Moreover, coordinated models improve social welfare under moderate subsidy levels by strengthening AI investment incentives. However, deeper coordination and higher subsidies may increase environmental impacts due to scale expansion effects, revealing a trade-off between economic benefits and environmental sustainability. These findings highlight the need for balanced subsidy and coordination strategies to promote AI adoption while ensuring sustainable development in power battery closed-loop supply chains.

Keywords: power battery; closed-loop supply chain; artificial intelligence; government subsidy; coordination

Mathematics Subject Classification: 90B06, 91A35

1. Introduction

In recent years, the development of new energy vehicles (NEVs) powered by lithium-ion batteries has been actively advanced by numerous countries. Due to their clean and efficient characteristics, NEVs are widely regarded as a core component of sustainable transportation development. For instance, the Netherlands, Germany, France, and the UK plan to prohibit all gasoline vehicles by 2040 [1]. However, the widespread adoption of NEVs results in an increasing number of retired power batteries. The China Automotive Technology Research Center estimates that the nationwide volume of retired power batteries will reach nearly 6 million tons by 2030. Therefore, improving the recycling and reutilization of retired power batteries has become a critical challenge for the sustainable development of power battery closed-loop supply chains (CLSCs).

The modern EV power battery manufacturing sector acknowledges research and development as a fundamental pillar of corporate strategic growth [2]. Thus, an increasing number of manufacturers have adopted AI-enabled systems to improve battery production and lifecycle management. AI facilitates data-driven battery condition monitoring, intelligent recycling classification, and real-time operational decision-making, thereby enhancing the efficiency of battery collection, remanufacturing, and second-life utilization [3,4]. Industrial practice reflects this trend. For example, CATL has integrated AI into battery manufacturing to support intelligent quality inspection, process optimization, and lifecycle traceability. Beyond improving operational efficiency, AI also reduces information asymmetry among supply chain members and creates additional value throughout the battery lifecycle. However, these benefits are often shared across the supply chain, whereas the associated investment costs are typically borne by individual firms. This mismatch between investment costs and distributed benefits weakens firms' incentives to adopt AI, highlighting the need for effective coordination mechanisms and appropriate policy support.

Despite its significant operational benefits, AI adoption is characterized by substantial upfront investment and uncertain payback periods. Consequently, firms may underinvest in AI even when it improves long-term operational performance. Government subsidies have therefore been widely adopted to encourage AI investment by reducing firms' effective investment costs. In recent years, many countries and regions have introduced financial support programs to accelerate industrial digitalization and AI deployment in manufacturing industries. For instance, Shanghai provides subsidies of up to 30% of approved investment for eligible AI frontier projects, while Shenzhen supports enterprises engaged in AI-based research and development activities. Similar policies have also been implemented in the United States, the European Union, Japan, and India. Although such policies strengthen firms' incentives to adopt AI, they do not fully address the incentive mismatch in closed-loop supply chains, where the costs of AI investment are typically borne by individual firms while the resulting operational benefits are shared among multiple supply chain members. Consequently, government subsidies alone may be insufficient to achieve efficient AI investment, highlighting the need for effective supply chain coordination mechanisms.

Although government subsidies reduce firms' effective AI investment costs, they do not fully eliminate investment disincentives in power battery closed-loop supply chains. Because AI-generated benefits are often shared among multiple supply chain members, firms undertaking AI investment cannot fully appropriate the resulting gains, leading to underinvestment. To address this problem, supply chain coordination mechanisms, such as cost-sharing and revenue-sharing contracts, have been widely adopted to better align investment costs with operational benefits. Existing studies have shown that these mechanisms enhance technology adoption and improve overall supply chain performance [5,6]. Therefore, both government intervention and contractual coordination are important for encouraging AI investment and improving closed-loop supply chain efficiency.

However, existing studies have primarily examined government subsidies, AI investment, and supply chain coordination in isolation. In practice, these factors are closely intertwined. Government subsidies directly affect firms' incentives to invest in AI, whereas coordination mechanisms determine how investment costs and technology benefits are distributed among supply chain members. Their interaction therefore plays a critical role in shaping firms' investment decisions and overall supply chain performance. Nevertheless, little is known about how different coordination mechanisms perform under government subsidy schemes or whether subsidies alter the effectiveness of alternative coordination contracts. Addressing this issue is particularly important for power battery closed-loop supply chains where substantial AI investment level. We develop a game-theoretic model incorporating government subsidies and compare alternative coordination mechanisms to examine their impacts on AI investment, pricing decisions, supply chain profits, and social welfare. Motivated by the aforementioned issues, we mention the following research questions:

(1) How does AI technology adoption influence operational decision-making in the CLSC for power batteries?

(2) How can government subsidies and coordination contracts be designed to allocate AI investment costs and enhance AI investment efficiency?

(3) What are the economic, environmental, and social welfare effects of AI investment under different coordination mechanisms and government subsidies?

The main contributions of this study are summarized as follows:

(1) Our study identifies and models the unique investment incentive mechanism associated with AI adoption in power battery closed-loop supply chains. Unlike conventional technology investments, AI investment generates substantial benefit spillovers through information sharing, intelligent decision-making, and lifecycle optimization, while its implementation costs are primarily borne by individual firms. This cost-benefit mismatch creates a distinct AI investment underinvestment problem that has not been sufficiently explored in existing CLSC literature. By endogenizing AI investment decisions, this study provides new theoretical insights into how AI-specific spillover effects influence supply chain members' strategic behaviors.

(2) We construct a unified analytical framework incorporating government subsidy schemes and contractual coordination arrangements to examine how external policy incentives interact with internal supply chain governance to mitigate AI investment inefficiencies. Specifically, three Stackelberg game models, including independent AI investment, cost-sharing coordination, and revenue-cost sharing coordination, are constructed to characterize different approaches for reallocating AI investment costs and AI-generated benefits. The results reveal the underlying mechanism through which coordination contracts mitigate free-riding incentives and enhance AI adoption under different subsidy conditions.

(3) Departing from prior research that concentrates predominantly on the economic outcomes of firms, we expand the analytical scope of closed-loop supply chain studies to examine the environmental and social welfare impacts of AI investment coordination. The analysis reveals that stronger coordination does not necessarily lead to superior environmental outcomes because the scale expansion induced by intensive AI adoption may offset efficiency improvements. These findings enrich the understanding of the trade-offs between technological upgrading, supply chain

coordination, and sustainability performance, while providing policy implications for designing effective subsidy and coordination strategies.

The subsequent sections are structured in the following manner. Section 2 provides a review of the related literature. Section 3 outlines the model setup used in this study. Section 4 presents the comparative results of the three models and provides an analysis. Section 5 displays numerical results to validate the approach and demonstrate the effectiveness of the proposed methods. Section 6 extends the analysis to environmental impact, social welfare, demand enhancement through AI-specific functionalities, and recycling quantity. Section 7 presents our main findings and future research.

2. Literature review

Our research evaluates the literature from three perspectives: AI technology in CLSC, effects of government subsidy in CLSC, and coordination mechanisms in CLSC.

2.1. AI technology in CLSC

The rapid growth of new energy vehicles has substantially increased the importance of efficient battery recycling, remanufacturing, and cascade utilization. To address these challenges, AI technologies have gradually become an important enabler of recycling efficiency and sustainable development in power battery CLSCs.

Existing studies have extensively demonstrated the operational benefits of AI in battery recycling and remanufacturing. AI technologies improve forecasting accuracy, battery state assessment, intelligent sorting, and resource allocation efficiency [7,8]. Focusing specifically on battery recycling, Antony Jose et al. [3] systematically reviewed the operational applications of AI and showed that computer vision enables automated battery identification and classification, machine learning enhances material composition analysis and recovery prediction, and intelligent robotic systems improve the efficiency and safety of battery disassembly. Through these capabilities, AI enhances both economic and environmental performance by improving recycling efficiency, remanufacturing quality, and resource utilization across battery CLSCs.

Beyond operational optimization, AI also generates value at the supply chain level by facilitating information sharing and coordination among participating firms. Li et al. [9] demonstrated that generative AI promotes knowledge sharing and supports circular economy practices, thereby strengthening AI-enabled operational capabilities. Wu et al. [10] and Yang and Liu [11] further showed that AI reduces coordination costs and improves supply chain resilience, while Lee et al. [12] found that AI-enabled digital solutions significantly enhance environmental performance when combined with green financing initiatives. Using large-scale empirical evidence from the automotive industry, Yanginlar et al. [13] confirmed that AI adoption partially mediates the relationship between reverse logistics implementation and sustainable supply chain performance, simultaneously improving environmental, economic, and social outcomes. Similar conclusions have also been reported in studies on AI-enabled operational optimization and sustainable supply chain management [14,15]. Collectively, these studies suggest that AI creates value not only through operational improvements but also by strengthening collaboration and information integration across CLSCs.

Despite the growing evidence regarding the operational and supply chain value of AI, most existing studies implicitly assume that AI capability is exogenously available once firms decide to adopt the technology. In reality, implementing AI requires substantial upfront investment. Zhu et al. [16]

argued that high development costs and the burden of sharing technical service expenses constitute major barriers to firms' AI investment. More importantly, the benefits generated by AI adoption are often shared among multiple supply chain members. Such benefit spillovers create a mismatch between investment costs and realized returns, allowing non-investing firms to benefit from AI adoption without bearing the associated costs. As a result, firms investing in AI may fail to appropriate the full value of their investments, leading to underinvestment in AI technologies. Although this investment incentive problem has important implications for power battery CLSCs, it remains insufficiently explored in the existing literature.

2.2. Effects of government subsidy in CLSC

Government subsidies have been widely adopted as an important policy instrument to encourage technological innovation in closed-loop supply chains. By reducing firms' effective investment costs and improving expected returns, subsidy policies can stimulate technology adoption, promote battery recycling, and enhance overall supply chain performance. Consequently, the design and effectiveness of government subsidies have attracted extensive attention in the CLSC literature.

Existing studies have mainly investigated government subsidy policies from three perspectives: subsidy targets, subsidy design, and market structures. Regarding subsidy targets, studies have shown that the choice of subsidy recipient substantially affects policy effectiveness. Guo and Yang [17] developed a CLSC model with third-party battery recycling under dynamic subsidy schemes and compared subsidies directed to manufacturers, recyclers, and both simultaneously. Their results showed that when the dynamic subsidy coefficient exceeds a critical threshold, subsidizing third-party recyclers generates the highest environmental and economic benefits. These findings indicate that selecting appropriate subsidy recipients is essential for improving policy efficiency.

Beyond subsidy recipients, a growing body of research has emphasized the importance of subsidy design. Chu et al. [18] systematically compared four representative government policies, including quantity-based subsidies, capacity-based subsidies, deposit-refund policies, and reward-penalty mechanisms, in power battery CLSC. Their analysis suggested that different policy instruments generate distinct incentive effects. For example, quantity-based subsidies primarily increase recycling activities but provide limited incentives for technological innovation, whereas capacity-based subsidies encourage battery performance improvement but contribute less to reverse logistics coordination. Furthermore, empirical evidence indicates that R&D subsidies and green innovation subsidies effectively promote firms' digital transformation and technological upgrading [19,20], providing an important policy foundation for encouraging AI investment.

The effectiveness of subsidy policies is also influenced by market characteristics. Cao and Mu [21] investigated subsidy policies in the highly fragmented e-bike battery recycling market and compared subsidies directed toward battery holders and recyclers. Their study identified a critical environmental governance cost threshold beyond which subsidies substantially improve recycling performance while reducing government expenditure. Moreover, subsidies targeted at recyclers were shown to generate stronger price incentives, higher recycling volumes, lower administrative costs, and superior Pareto improvements than subsidies provided directly to dispersed battery holders. These findings suggest that market structure should be explicitly considered when designing subsidy policies.

Overall, the existing literature consistently demonstrates that well-designed government subsidies can improve recycling performance, profitability, environmental sustainability, and social welfare under various CLSC settings [18,22,23]. Moreover, differentiated subsidy schemes generally outperform uniform subsidy policies because they better accommodate heterogeneous operational conditions and incentive structures across supply chains [18,23].

Despite these advances, existing studies primarily focus on the direct impacts of government subsidies on firms' innovation activities and operational performance, while paying relatively limited attention to their interaction with AI investment incentives. In practice, AI adoption generates substantial benefit spillovers through improved information sharing, operational coordination, and recycling efficiency, whereas the associated investment costs are often borne by only one supply chain member. Consequently, even under government subsidy schemes, firms may still underinvest in AI because they cannot fully appropriate the resulting benefits. Whether government subsidies can effectively mitigate this investment disincentive, and how they interact with alternative supply chain coordination mechanisms, remains largely unexplored in the power battery CLSC.

2.3. Coordination mechanisms in CLSC

Because government subsidies alone cannot completely eliminate the mismatch between investment costs and shared benefits, supply chain coordination mechanisms have become an important complementary governance approach in closed-loop supply chains. By reallocating costs, revenues, and operational responsibilities among participating firms, coordination contracts help improve incentive alignment and enhance overall supply chain performance.

Existing studies have shown that combining government intervention with contractual coordination can further improve CLSC performance. Guo and Yang [17] proposed a coordination mechanism based on recycling-rate benchmarks and derived the minimum dynamic subsidy intensity required for different subsidy schemes to achieve the efficiency of centralized decision making. Their results further indicated that the effectiveness of coordination depends on recycling difficulty, suggesting that governments should shift subsidy priorities toward battery manufacturers as recycling costs increase. Similarly, Chu et al. [18] argued that subsidy policies alone are insufficient to coordinate power battery CLSCs and therefore developed a bidirectional policy combining forward production subsidies with reverse reward-penalty mechanisms. Their study demonstrated that integrating subsidy policies with coordination mechanisms simultaneously improves technological innovation, recycling performance, and both economic and environmental outcomes. These studies collectively suggest that government subsidies and coordination mechanisms should be designed jointly rather than independently.

Beyond policy coordination, a substantial body of research has investigated contractual coordination in conventional power battery CLSCs. Zhao et al. [24] demonstrated that centralized decision making and bidirectional cost-sharing contracts improve recycling volumes and supply chain profitability, while Khodoomi et al. [25] showed that hierarchical cost-sharing contracts effectively coordinate lifecycle decisions among supply chain members. Lin et al. [26] further compared five cooperative strategies in a tripartite Stackelberg game involving manufacturers, retailers, and third-party recyclers, confirming that grand coalition cooperation achieves the highest system performance and that Shapley value-based profit allocation effectively stabilizes cooperation. Their analysis also revealed that combining reward-penalty mechanisms with cap-and-trade policies further strengthens cooperative recycling performance. In addition, Xiang and Xu [27] highlighted the role of Internet recycling platforms in reshaping channel power and improving recycling efficiency, whereas Lyu et al. [28] and Liu et al. [29] emphasized the benefits of collaborative recycling involving manufacturers and third-party recyclers. Collectively, these studies establish a solid theoretical foundation for operational coordination in battery CLSCs.

More recently, researchers have begun to extend coordination mechanisms from operational decisions to technology investment. Existing evidence suggests that cost-sharing and revenue-sharing contracts can improve firms' innovation incentives by redistributing investment costs and innovation benefits among supply chain members [14,15]. However, current research in battery recycling has focused primarily on blockchain traceability rather than AI investment. For example, Xu et al. [30] incorporated blockchain investment costs and environmental governance costs into a CLSC coordination framework and compared three cost-sharing mechanisms, namely no cost sharing, blockchain cost sharing, and total cost sharing. Their results showed that jointly sharing technology and environmental costs substantially strengthens firms' technology investment incentives while improving supply chain profitability. Extending this perspective, Mostafavi et al. [31] investigated differentiated contractual arrangements among blockchain service providers, manufacturers, battery suppliers, and recyclers, demonstrating that appropriately designed cost-sharing and profit-sharing contracts effectively reduce free-riding behavior arising from technology benefit spillovers. Furthermore, several studies have suggested that coordination contracts and government subsidies may jointly enhance supply chain efficiency and sustainability performance [32,33].

Despite these advances, the existing literature has largely concentrated on operational coordination, pricing decisions, and blockchain-based technology investment. Comparatively little attention has been paid to AI investment, despite its stronger data dependence, more pronounced network externalities, and broader benefit spillovers across supply chain members. Consequently, it remains unclear whether conventional coordination mechanisms can effectively mitigate AI investment disincentives under government subsidy schemes. In particular, the relative effectiveness of alternative coordination arrangements in promoting AI adoption and improving the economic, environmental, and social performance of power battery CLSCs has yet to be systematically investigated.

2.4. Research gap

Although existing studies have extensively explored AI technologies, government subsidies, and coordination mechanisms in closed-loop supply chains, several important theoretical limitations remain. Prior research on AI-enabled CLSCs mainly focuses on the operational benefits of AI adoption, treating AI capability as an exogenous condition rather than an endogenous investment decision. Meanwhile, CLSC coordination literature generally examines how cost-sharing and revenue-sharing mechanisms improve operational efficiency by reallocating costs and benefits among supply chain members. However, the introduction of AI investment challenges this traditional coordination perspective because AI generates value spillovers, while its investment costs are concentrated on individual firms. This mismatch between investment costs and shared benefits creates an AI-specific investment externality that may lead to underinvestment.

Furthermore, existing studies on government subsidies and contractual coordination mainly investigate their individual effects on technology adoption or supply chain performance. It remains unclear whether and how these governance mechanisms can jointly address AI-induced investment externalities. In particular, the effectiveness of traditional coordination contracts under government subsidy policies, and their implications for economic, environmental, and social performance, have not been fully understood. Our study extends CLSC coordination theory from operational coordination to AI investment coordination by developing an endogenous AI investment framework under government subsidy policies. Specifically, we investigate how cost-sharing and revenue-cost sharing mechanisms reshape AI investment incentives and how government subsidies interact with coordination mechanisms to mitigate AI underinvestment in power battery CLSC. Table 1 summarizes the key differences between our study and the existing literature.

Table 1. Comparison with prior literature.

Literature	CLSC coordination	AI technology	Government subsidy	Contract mechanism
Xiang and Xu (2020)	√			
Hua et al. (2023)		√	√	
Zhang et al. (2023)	√		√	
Antony Jose et al. (2024)		√		
Zhang et al. (2024)	√	√		
Li et al. (2024)		√		
Cao and Mu (2025)	√		√	
Yang and Liu (2025)	√	√		√
Zhao et al. (2025)	√			√
Khodoomi et al. (2025)	√			√
Chu et al. (2025)	√		√	
Guo et al.（2025)		√	√	
Wu et al. (2025)	√	√		
Guo and Yang (2026)	√		√	√
Lin et al. (2026)	√			√
Zhu et al. (2026)		√		
Mostafavi et al. (2026)	√			√
Yanginlar et al. (2026)	√	√		
Xu et al. (2026)	√			√
This paper	√	√	√	√

3. The model

In this section, three collaboration models for power battery CLSC are first described. Subsequently, the foundational assumptions and notations deployed in the subsequent sections are explained. Accordingly, a performance evaluation structure is established to assess CLSC members under the different coordination mechanisms.

3.1. Problem description

We consider a power battery closed-loop supply chain for new energy vehicles, consisting of a power battery supplier, an NEV manufacturer, and end consumers. The CLSC includes both forward and reverse logistics to capture the complete battery lifecycle. In the forward supply chain, the supplier produces AI-enabled power batteries and sells them to the manufacturer, who assembles and markets NEVs to consumers. In the reverse supply chain, the manufacturer collects end-of-life batteries, classifies them according to their remaining capacity, allocates qualified batteries to cascade utilization, and transfers the remaining batteries to the supplier for material recovery and remanufacturing.

The supplier possesses technological advantages in battery research and development, large-scale manufacturing, and AI deployment, and therefore acts as the Stackelberg leader. The manufacturer is the Stackelberg follower. Following the government's announcement of the AI subsidy policy, the supplier determines the AI investment level and wholesale price, after which the manufacturer decides the retail price of NEVs and the battery take-back price. This sequential decision process reflects the vertical decision structure commonly observed in the power battery industry and captures the strategic interaction between upstream technology investment and downstream pricing and recycling decisions.

The decisions of the two firms are mutually dependent. The supplier's AI investment improves battery production while influencing the manufacturer's procurement cost through the wholesale price. In turn, the manufacturer's pricing and recycling decisions determine market demand and battery return volumes, thereby affecting the supplier's production scale and the economic returns to AI investment. To encourage technological innovation, the government provides subsidies for AI investment, which partially offset the supplier's investment costs and influence firms' strategic decisions.

To investigate how different collaboration mechanisms affect AI investment incentives and supply chain performance, we consider three coordination scenarios under the above decision framework. The independent AI investment model (Model N) serves as the benchmark decentralized scenario in which the supplier independently bears all AI investment costs. The cost-sharing model (Model C) allows the manufacturer to share part of the supplier's AI investment cost, thereby mitigating the investment burden. Building on Model C, the revenue-cost sharing model (Model J) further introduces a revenue-sharing contract to strengthen downstream participation and better align investment costs with operational benefits. Comparing these three scenarios enables us to evaluate the effectiveness of alternative coordination mechanisms under government subsidy policies.

(1) Independent AI investment model. The supplier bears the full AI investment cost, with government subsidy partially reducing the burden. The manufacturer focuses on NEV sales and battery recycling, without sharing investment costs. The framework of the model is illustrated in Figure 1.

(2) Cost-sharing model. The supplier and manufacturer jointly share the AI investment cost. All other operational decisions follow the same structure as the independent model. This model is presented in Figure 2.

(3) Revenue-cost sharing model. The manufacturer undertakes partial AI investment cost and transfers a portion of NEV sales revenue to the supplier. This combined mechanism enhances collaborative incentives, supported by government subsidy. The structure of the proposed model is shown in Figure 3.

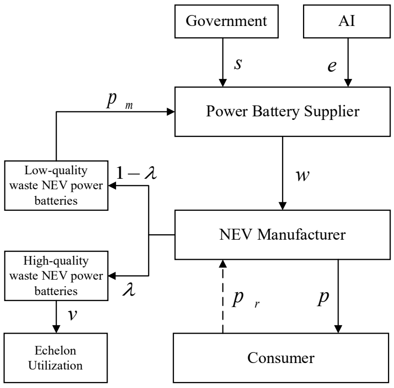


Figure 1. Independent model.

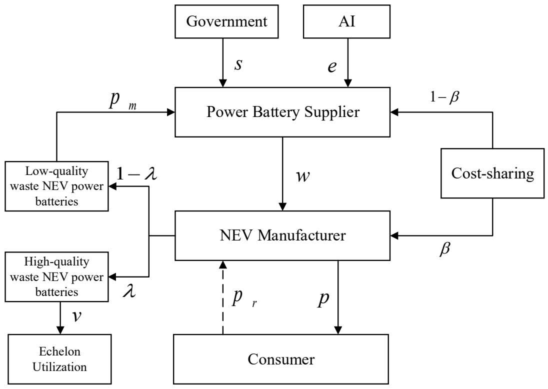


Figure 2. Cost-sharing model.

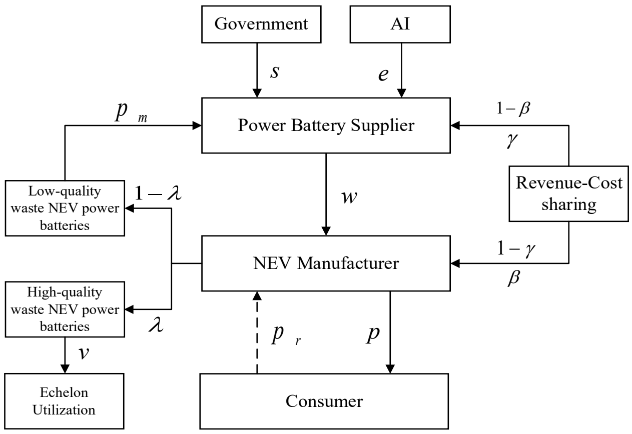


Figure 3. Revenue-cost sharing model.

Following Hua et al. [20] and Bai et al. [34], market demand is assumed to decrease linearly with the retail price of NEVs. Meanwhile, AI investment improves battery performance, operational reliability, and lifecycle management, thereby increasing consumers' willingness to purchase AI-enabled battery products [23,35]. Consequently, market demand is assumed to increase linearly with the AI investment level. The demand function is therefore given by $d = a - bp + \rho e$, where a denotes the potential market size, b is the price sensitivity coefficient, and ρ represents consumers' sensitivity to AI-enabled product improvements.

Consumers incur time and inconvenience costs when returning retired batteries. Following Jia et al. [6] and Feng et al. [36], consumers participate in battery recycling only when the take-back price exceeds their individual return willingness. Let t denote consumers' return willingness. Consistent with the Extended Producer Responsibility framework, we assume that the manufacturer is responsible for battery collection, whereas the supplier undertakes cascade utilization and material recovery. Furthermore, assuming there is no competition for recycling between the manufacturer and the supplier. The consumer surplus derived from returning retired power batteries is denoted as $p_r - t$. Consumers will be willing to return retired power batteries only when $p_r - t > 0$. Consequently, the quantity of retired power batteries recycled from consumers by the manufacturer can be expressed as $q = \int_0^{p_r} f(t)dt = p_r$, reflecting a positive relationship between the recycling price and the return volume [6,36]. To ensure consistency with the fundamental operational logic of closed-loop supply chains, we impose $q < d$ on the recycling quantity, which stipulates that the volume of collected retired batteries cannot exceed the total sales volume of power batteries in the market.

Let e denote the supplier's AI investment level, which captures the extent to which AI is deployed throughout battery production, operation, and recycling processes [37]. A higher AI investment level enhances product quality and operational efficiency but also requires greater expenditures on algorithm development, data infrastructure, computing resources, and intelligent equipment. Following Zhang et al. [38], the AI investment cost is assumed to be a convex function, especially represented by $\frac{1}{2}ke^2$, where k denotes the cost coefficient of AI technology investment. A larger value of k implies a higher marginal cost of AI investment.

3.2. Notation

The notations provided in table 2 below are consistently used throughout this paper.

Table 2. Notations.

Notations	Description
Model parameters	
a	Market size
b	Consumer sensitivity coefficient of retail price
c	Unit production cost of power battery
c_r	Unit remanufacture cost of power battery
ρ	Consumer sensitivity coefficient of AI-driven product
k	Cost coefficient of AI investment level
v	Unit value of high-quality waste power battery
λ	Proportion of high-quality waste power batteries
β	Cost-sharing ratio
γ	Revenue-sharing ratio

Continued on next page

Notations	Description
s	Government subsidy coefficient of AI investment level
Decision variables	
w	Unit wholesale price of the power battery supplier
p	Unit retail price of the manufacturer
p_r	Unit recycling price of waste power battery
p_m	Unit buyback price of low-quality waste power battery
e	AI investment level
Function	
d	Market demand for NEVs
q	Recycling volume of waste power battery
π_s^i	Profit of power battery supplier (i = N, C, J)
π_m^i	Profit of NEV manufacturer (i = N, C, J)
E^i	Environmental impact (i = N, C, J)
CS^i	Consumer surplus (i = N, C, J)
SW^i	Social welfare (i = N, C, J)

*Note: N means independent AI technology investment model, C means cost sharing model, J means revenue-cost sharing model.

3.3. Problem formulation

This section formulates a closed-loop supply chain model under three AI investment settings, namely independent investment, cost-sharing, and revenue-cost sharing, to examine their effects on equilibrium decisions and system performance.

3.3.1. Independent AI technology investment by tattery supplier (Model N)

In this scenario, AI technology investment is independently undertaken by the power battery supplier, while a certain proportion of subsidies is provided by the government to support AI-driven technological advancement. Accordingly, the profit functions of the power battery supplier and NEV manufacturer are formulated as follows:

$$\pi_s^N = (w-c)[d-(1-\lambda)q]+(w-c_r-p_m)(1-\lambda)q-\frac{1}{2}(1-s)ke^2 \tag{1}$$

$$\pi_m^N = (p-w)d + q[\lambda v + (1-\lambda)p_m - p_r] \tag{2}$$

The above game model is solved using the inverse solution method, as presented in Table 3. (the proofs can be seen in the Appendix A).

Table 3. Equilibrium solutions under independent AI technology investment by battery supplier.

Variable	Equilibrium solutions
e	$\dfrac{(bc-a)\rho}{4bk(-1+s)+\rho^2}$
w	$\dfrac{2(a+bc)k(-1+s)+c\rho^2}{4bk(-1+s)+\rho^2}$
p	$\dfrac{(3a+bc)k(-1+s)+c\rho^2}{4bk(-1+s)+\rho^2}$
p_r	$\dfrac{c+c_r(-1+\lambda)-c\lambda+v\lambda}{4}$
p_m	$\dfrac{-c+c_r+c\lambda-c_r\lambda+v\lambda}{2(-1+\lambda)}$
π_s^N	$\dfrac{1}{8}\left((c+c_r(-1+\lambda)-c\lambda+v\lambda)^2+\dfrac{4(a-bc)^2k(-1+s)}{4bk(-1+s)+\rho^2}\right)$
π_m^N	$\dfrac{1}{16}(c_r+c(-1+\lambda)-(c_r+v)\lambda)^2+\dfrac{b(a-bc)^2k^2(-1+s)^2}{(4bk(-1+s)+\rho^2)^2}$

3.3.2. Cost sharing (Model C)

Under the government subsidy scheme, the power battery supplier and the NEV manufacturer jointly invest in AI technologies. This investment aims to enhance technological efficiency and strengthen market competitiveness. AI capabilities increasingly serve as key enablers of product intelligence, operational safety, and life-cycle environmental performance in new energy vehicles. The level of AI investment in power batteries thus critically influences both product quality and sustainability outcomes. In this collaborative framework, the automobile manufacturer covers a designated share of the AI investment, while the battery supplier assumes the remaining portion. This arrangement balances technological risks and promotes coordinated AI-driven innovation across the CLSC. Consequently, the profits for the power battery supplier and NEV manufacturer are expressed as follows:

$$\pi_s^C = (w-c)[d-(1-\lambda)q] + (w-c_r-p_m)(1-\lambda)q - \frac{1}{2}(1-s-\beta)ke^2 \quad (3)$$

$$\pi_m^C = (p-w)d + q[\lambda v + (1-\lambda)p_m - p_r] - \frac{1}{2}\beta ke^2 \quad (4)$$

The equilibrium solutions under the cost-sharing model are derived by solving above game model using the inverse solution method, as shown in Table 4 (the proofs are provided in Appendix A).

Table 4. Equilibrium solutions under the cost-sharing model.

Variable	Equilibrium solutions
e	$\frac{(bc-a)\rho}{4bk(-1+s+\beta)+\rho^2}$
w	$\frac{2(a+bc)k(-1+s+\beta)+c\rho^2}{4bk(-1+s+\beta)+\rho^2}$
p	$\frac{(3a+bc)k(-1+s+\beta)+c\rho^2}{4bk(-1+s+\beta)+\rho^2}$
p_r	$\frac{c+c_r(-1+\lambda)-c\lambda+v\lambda}{4}$
p_m	$\frac{-c+c_r+c\lambda-c_r\lambda+v\lambda}{2(-1+\lambda)}$
π_s^C	$\frac{1}{8}\left((c+c_r(-1+\lambda)-c\lambda+v\lambda)^2+\frac{4(a-bc)^2k(-1+s+\beta)}{4bk(-1+s+\beta)+\rho^2}\right)$
π_m^C	$\frac{1}{16}(c_r+c(-1+\lambda)-(c_r+v)\lambda)^2+\frac{b(a-bc)^2k^2(-1+s+\beta)^2}{(4bk(-1+s+\beta)+\rho^2)^2}-\frac{(a-bc)^2k\beta\rho^2}{2(4bk(-1+s+\beta)+\rho^2)^2}$

3.3.3. Revenue-cost sharing (Model J)

Within the integrated revenue-cost sharing framework, the battery supplier and the automobile manufacturer jointly invest in AI technology. The manufacturer bears a fixed portion of the AI investment cost. In addition, it transfers part of its operating profit to the supplier as a revenue-sharing payment. This dual mechanism eases financial pressure on each party. It also aligns incentives for AI-driven innovation. As a result, technological improvement is more coordinated across the supply chain. Based on this setup, the profits of the power battery supplier and NEV manufacturer can be derived as shown below:

$$\pi_s^J = (w-c)[d-(1-\lambda)q] + (w-c_r-p_m)(1-\lambda)q - \frac{1}{2}(1-s-\beta)ke^2 + \gamma(p-w)d \tag{5}$$

$$\pi_m^J = (1-\gamma)(p-w)d + q[\lambda v + (1-\lambda)p_m - p_r] - \frac{1}{2}\beta ke^2 \tag{6}$$

The equilibrium solutions of the revenue-cost sharing model are derived by applying the inverse solution method to the above game framework, as shown in Table 5 (the proofs are provided in Appendix A).

Table 5. Equilibrium solutions under the revenue-cost sharing model.

Variable	Equilibrium solutions
e	$\frac{(a-bc)\rho}{2bk(-1+s+\beta)(-2+\gamma)-\rho^2}$
w	$-\frac{2k(-1+s+\beta)(a+bc-a\gamma)+c\rho^2}{2bk(-1+s+\beta)(-2+\gamma)-\rho^2}$
p	$-\frac{k(-1+s+\beta)(bc+a(3-2\gamma))+c\rho^2}{2bk(-1+s+\beta)(-2+\gamma)-\rho^2}$
p_r	$\frac{c+c_r(-1+\lambda)-c\lambda+v\lambda}{4}$
p_m	$\frac{-c+c_r+c\lambda-c_r\lambda+v\lambda}{2(-1+\lambda)}$
π_s^J	$\frac{1}{8}\left((c+c_r(-1+\lambda)-c\lambda+v\lambda)^2-\frac{4(a-bc)^2k(-1+s+\beta)}{2bk(-1+s+\beta)(-2+\gamma)-\rho^2}\right)$
π_m^J	$\frac{1}{4}(c_r+c(-1+\lambda)-(c_r+v)\lambda)^2-\frac{2b(a-bc)^2k^2(-1+s+\beta)^2(-1+\gamma)+2(a-bc)^2k\beta\rho^2}{(-2bk(-1+s+\beta)(-2+\gamma)+\rho^2)^2}$

4. Comparison and analysis

This section investigates AI technology investment decisions under the three proposed models and compares their broader implications. Specifically, we explore how AI investment is determined in the independent investment model, the cost-sharing arrangement, and the revenue-cost sharing mechanism. Building on these decision structures, we further evaluate the outcomes of each model. This assessment considers economic, environmental, and social welfare. The analysis provides a comprehensive understanding of their impacts on the CLSCs.

4.1. Economic efficiency analysis

We derive Proposition 1 through a comparison and analysis of the equilibrium solutions of AI technology investments under different scenarios.

Proposition 1: $e^{N*} < e^{C*} < e^{J*}$.

Proposition 1 indicates that, under the independent investment scenario, the supplier bears the full cost of AI investment. In this case, the supplier cannot internalize the downstream benefits generated by AI-driven improvements in battery performance. Consequently, the incentive to invest in AI technology is limited, resulting in a relatively low investment level. When a cost-sharing mechanism is introduced, the supplier's effective investment burden is reduced. This alleviation of cost pressure strengthens the supplier's willingness to increase AI investment. The revenue-cost sharing structure provides the strongest incentive for AI adoption. Under this arrangement, the supplier shares both the investment cost and the downstream revenue. This allows the supplier to appropriate a greater share of the value generated by AI adoption. As a result, the supplier chooses the highest level of AI investment among the three models. These theoretical results are consistent with observed industry practices. In particular, Contemporary Amperex Technology Co., Limited (CATL) collaborates with technology firms on AI-driven battery management systems. Through joint investment and benefit-sharing arrangements, algorithm optimization and performance improvement are accelerated. Such practices reflect the incentive mechanism implied by Proposition 1. They further demonstrate that coordinated investment schemes are effective in promoting technological upgrading.

Corollary 1: (1) $\frac{\partial e^{C*}}{\partial \beta} > 0, \frac{\partial e^{J*}}{\partial \beta} > 0, \frac{\partial e^{J*}}{\partial \gamma} > 0.$

(2) $\frac{\partial e^{N*}}{\partial k} < 0, \frac{\partial e^{C*}}{\partial k} < 0, \frac{\partial e^{J*}}{\partial k} < 0.$

(3) $\frac{\partial e^{N*}}{\partial \rho} > 0, \frac{\partial e^{C*}}{\partial \rho} > 0, \frac{\partial e^{J*}}{\partial \rho} > 0.$

(4) $\frac{\partial e^{N*}}{\partial s} > 0, \frac{\partial e^{C*}}{\partial s} > 0, \frac{\partial e^{J*}}{\partial s} > 0.$

Corollary 1 demonstrates that the principal structural parameters influence the supplier's AI investment. These effects are directionally consistent across the three decision frameworks. Stronger collaborative incentives promote higher investment. In the model C, an increased cost-sharing ratio lowers the supplier's effective marginal expenditure. In the model J, the combination of cost-sharing and revenue-sharing coefficients mitigates cost distortions and enhances the supplier's capture of downstream AI-driven gains. The AI cost coefficient negatively affects investment. Higher costs reduce the marginal return of AI input. In contrast, greater consumer sensitivity to AI encourages higher investment. Increased government subsidy intensity also raises investment by lowering the effective cost. Overall, sustained AI investment is best supported by incentive-aligned contractual arrangements. Such arrangements improve marginal returns and coordinate technological costs, market responsiveness, and policy support.

Proposition 2: (1) $w^{J*} < w^{N*} < w^{C*}$, if $0 < s < s_0$.

(2) $p^{J*} < p^{N*} < p^{C*}$, if $0 < s < s_1$.

Proposition 2 reveals that, when government subsidy remains within a moderate range, wholesale and retail prices differ across contractual modes. Prices are lowest under the revenue-cost sharing mode. They are moderate under the independent investment mode. They are highest under the cost-sharing mode. These differences stem from variations in cost-bearing structures and profit-sharing incentives. Under the revenue-cost sharing scheme, cooperation occurs on the cost as well as the revenue sides. Revenue sharing weakens the supplier's incentive to raise the wholesale price. Meanwhile, cost sharing together with downstream profit sharing incentivizes the manufacturer to reduce the retail price. The pricing strategy expands market demand and benefits both parties. Under the independent investment mode, coordination is absent. Each firm acts independently when making pricing decisions. The AI investment cost is therefore partially passed on through higher wholesale and retail prices. Under the cost-sharing contract, cooperation is unidirectional. The cost-sharing model alleviates the supplier's investment burden but does not align profit distribution. Both the supplier and the manufacturer retain strong incentives to increase prices. Consequently, wholesale and retail prices reach their highest levels in this mode. These pricing effects are most pronounced when government subsidies are relatively low. As subsidy levels increase, external financial support offsets internal cost pressures. The role of cooperative mechanisms in shaping price decisions is therefore weakened.

Proposition 3: (1) $\pi_s^{N*} < \pi_s^{C*} < \pi_s^{J*}$.

(2) $\pi_m^{N*} < \pi_m^{C*} < \pi_m^{J*}$, if $0 < \beta < \beta_0, 0 < \gamma < \gamma_0$.

Proposition 3(1) illustrates that the supplier's profit exhibits a stable ranking across the three models. Profit is lowest under the independent investment model. It increases under the cost-sharing model. It reaches its highest level under the revenue-cost sharing model. This ranking arises from differences in investment burden and value appropriation. Under the independent investment contract, the supplier bears the full AI cost. High investment pressure constrains AI investment. Value creation and demand expansion are therefore limited, resulting in weaker profit performance. The cost-sharing contract partially alleviates the supplier's financial burden. Reduced cost pressure supports a higher level of AI investment. Improved battery performance enhances product value and market demand. Supplier profit consequently increases. The revenue-cost sharing contract arrangement provides the strongest profit incentive. In this model, the supplier benefits from both cost reduction and downstream revenue participation. This dual incentive enhances the supplier's ability to capture value generated by AI adoption. As a result, supplier profit is maximized among the three models. These findings indicate that coordinated AI investment mechanisms are effective in CLSC. Such mechanisms enhance value creation and strengthen incentives for AI investment.

Proposition 3 (2) shows that, when $0<\beta<\beta_0$, $0<\gamma<\gamma_0$, the automobile manufacturer's profit is highest under the revenue-cost sharing model, followed by the cost-sharing model, and lowest under the independent investment model. This pattern arises from differences in AI cost pass-through, value transmission efficiency, and the distribution of collaborative gains. In particular, AI investment enhances battery performance and supply chain efficiency, thereby enhancing consumers' valuation of new energy vehicles and stimulating market demand, which ultimately enlarges the total value created within the supply chain. To recover AI investment costs, firms adjust pricing strategies across governance modes. Under independent investment, the supplier passes AI costs via higher wholesale prices, severely squeezing the manufacturer's profit and weakening its incentive to support further AI deployment. Under cost sharing, partial cost allocation moderates price pass-through and allows the manufacturer to benefit from demand expansion, though the absence of revenue sharing constrains value capture. Consequently, the revenue-cost sharing mode yields the highest manufacturer profit. Cost-sharing curbs the incentive for cost pass-through. Revenue-sharing stimulates greater AI investment by the supplier. By contrast, profits under the other two modes are lower. This is due to incomplete coordination and inefficient allocation of AI-driven value.

Corollary 2: (1) $\frac{\partial \pi_s^{N*}}{\partial s}>0, \frac{\partial \pi_s^{C*}}{\partial s}>0, \frac{\partial \pi_s^{J*}}{\partial s}>0.$

(2) $\frac{\partial \pi_m^{N*}}{\partial s}>0.$ When $0<s<1-3\beta, \frac{\partial \pi_m^{C*}}{\partial s}>0.$

When $0<s<\frac{3\beta-2\beta\gamma+\gamma-1}{\gamma-1}, \frac{\partial \pi_m^{J*}}{\partial s}>0.$

Corollary 2 demonstrates that government subsidies boost the profits of battery suppliers across all AI investment scenarios, as they reduce AI investment costs while enhancing the returns generated from collaborative innovation. In contrast, the impact of government subsidies on manufacturers is conditional: manufacturer profits increase only within a specific subsidy range, whereas excessive subsidies tend to distort collaboration incentives and thereby erode profitability. These findings underscore the necessity of designing precisely calibrated subsidy policies that can effectively facilitate AI investment and supply chain coordination. From a management perspective, these conclusions provide meaningful insights for both policymakers and supply chain participants. The policymakers should abandon uniform subsidy strategies and instead adopt targeted designs that differentiate between battery suppliers and manufacturers, such as providing stable subsidy support for suppliers to sustain their AI investment enthusiasm while setting clear upper limits for manufacturers' subsidy and establishing real-time monitoring mechanisms to avoid incentive distortion. For the supply chain managers, battery suppliers can leverage subsidy-driven cost advantages to accelerate AI technology R&D and deepen collaborative innovation with manufacturers, while manufacturers need to conduct in-depth cost-benefit analysis to identify the optimal subsidy range for their own operations, avoid over-reliance on policy support, and maintain the initiative in collaborative relationships. Both parties should strengthen communication with policymakers to feed back the actual effect of government subsidies, forming a policy-enterprise interaction mechanism that promotes the supply chain's sustainable development.

4.2. Environmental benefit analysis

This section evaluates the environmental consequences of supply chains under the three proposed models using a comprehensive life cycle approach. Following the research of Esenduran et al. [39], the life cycle of power batteries comprises three stages: the production phase, the usage phase by consumers, and the end-of-life disposal of unrecovered power batteries. The production phase includes the manufacture of new battery materials as well as the recycling and secondary utilization of retired batteries. We assumed that the environmental impact associated with each phase can be quantified on a per-unit basis, which is represented by $\tau_m, \tau_r, \tau_t, \tau_c, \tau_u$, correspondingly. Detailed metrics for the environmental impact at each stage of the battery life cycle are provided in Table 6.

Table 6. Environmental effects associated with each stage of the power battery life cycle (i = N, C, J).

Section	Environmental impact
New material production stage of power battery	$[d^i-(1-\lambda)q^i]\tau_m$
Reuse Stage of power battery	$(1-\lambda)q^i\tau_r$
Echelon utilization stage of power battery	$\lambda q^i\tau_t$
Consumer use of power battery stage	$d^i\tau_c$
Consumer self-disposal stage	$(d^i-q^i)\tau_u$

The overall environmental impact of the power battery over its life cycle is derived by summing the impacts across the five stages listed in Table 6, as detailed below:

$$E^i=[d^i-(1-\lambda)q^i]\tau_m+(1-\lambda)q^i\tau_r+\lambda q^i\tau_t+d^i\tau_c+(d^i-q^i)\tau_u \tag{7}$$

By substituting into the equilibrium solutions, the following conclusions are drawn:

Proposition 4: $E^{N*}<E^{C*}<E^{J*}$.

Proposition 4 indicates that the environmental effects of the power battery CLSC differ across AI investment models. The impact is lowest under independent AI investment, increases under the cost-sharing model and reaches its highest level under the revenue-cost sharing model. This pattern is driven by differences in AI investment intensity and scale expansion effects. Under independent investment, high-cost pressure limits AI investment. Firms focus on efficiency-oriented applications. Capacity expansion and resource consumption remain constrained. Environmental impact is therefore relatively low. On the other hand, under the cost-sharing model, individual investment pressure is partially alleviated. Firms are encouraged to adopt moderate AI upgrades. Production and recycling activities expand incrementally. Resource and energy use increase accordingly, leading to a moderate rise in environmental impact. The revenue-cost sharing model generates the strongest expansion incentive. Shared costs and shared revenues substantially reduce investment risk. Firms engage in aggressive AI investment. Large scale production and recycling expansion follow. The resulting growth in resource and energy demand outweighs AI-driven efficiency gains. Consequently, environmental impact reaches its highest level in this model. These results highlight a potential trade-off between coordination-driven expansion and environmental performance in AI-driven CLSC.

Corollary 3: $\frac{\partial E^{N*}}{\partial s} > 0, \frac{\partial E^{C*}}{\partial s} > 0, \frac{\partial E^{J*}}{\partial s} > 0.$

Corollary 3 confirms that government subsidies, despite their intention to accelerate AI investment, tend to intensify environmental impacts across all decision models. The underlying mechanism is scale expansion: government subsidies ease firms' financial constraints, enabling higher production and recycling volumes that increase resource use and energy consumption, often offsetting the efficiency gains generated by AI. This outcome highlights the dual nature of subsidy in closed-loop systems. While they promote technological upgrading, they may also amplify environmental pressures if applied without ecological safeguards. To mitigate these risks, firms and policymakers should incorporate explicit environmental criteria into subsidy-supported decisions, integrate AI-based monitoring tools, and tie policy incentives to verifiable environmental performance to ensure that innovation-driven growth remains aligned with long-term sustainability objectives.

4.3. Social benefit analysis

In this research, according to Esenduran et al. [39], consumer surplus refers to the difference between consumer utility and actual expenditure when consuming a certain quantity of products. Therefore, the consumer surplus is:

$$CS_i = \int_0^{d^{i*}} f(d^i)dd^i - p^{i*}d^{i*}, f(d^i) = \frac{a - d^i + \rho e}{b} \tag{8}$$

To evaluate the overall performance of the CLSC under different coordination mechanisms, we employ social welfare as the system level performance measure. Following Wu and Zhou [40], social welfare is defined as the sum of the total profit of supply chain members and consumer surplus. The total profit includes the profits of the supplier and the manufacturer, while consumer surplus captures the net utility obtained by consumers in the product market. Accordingly, the social welfare under the three coordination scenarios is expressed as follows:

$$SW^i = \pi_s^i + \pi_m^i + CS^i \tag{9}$$

Proposition 5: $SW^{N*} < SW^{C*} < SW^{J*}$, if $0 < \beta < \beta_1, 0 < \gamma < \gamma_1$.

Proposition 5 states that social welfare differs across AI investment models when cost-sharing and revenue-sharing ratios fall within certain ranges. Social welfare is highest under the revenue-cost sharing model. It is moderate under the cost-sharing mode. It is lowest under the independent investment model. These differences arise from the degree of coordination in AI investment and benefit allocation. In the revenue-cost sharing model, cost sharing reduces the supplier's financial burden. At the same time, revenue sharing motivates the manufacturer to participate in supply chain upgrading. This bilateral coordination supports broader AI deployment across production and recycling activities. Overall efficiency improves. Consumer experience and firm profits also increase. Social welfare is therefore maximized. In the cost-sharing model, coordination is partial. Shared costs alleviate the supplier's funding pressure. However, the absence of revenue sharing limits the manufacturer's incentive to engage in AI investment. The diffusion of AI benefits along the supply chain is constrained. Social welfare increases only moderately. In the independent investment model, coordination is absent. The supplier bears the full AI investment cost. AI deployment is restricted to core production activities. Benefits are not fully transmitted to manufacturers or consumers. As a result, social welfare reaches its lowest level among the three models.

5. Numerical analysis

This section presents numerical analyses to illustrate the equilibrium outcomes of the three coordination models and examine how key parameters affect firms' decisions and the overall performance of the power battery closed-loop supply chain.

5.1. Background information

Numerical simulations are conducted in Mathematica to validate the analytical results and examine the underlying mechanisms of the proposed models. To improve the practical relevance of the numerical analysis, the model parameters are calibrated using data from three representative battery electric vehicles in the market, namely the BYD Qin PLUS EV, Tesla Model X 100D, and BAIC EU400. These vehicles represent different market segments and battery technologies, providing a representative basis for estimating the economic parameters of power battery production, remanufacturing and echelon utilization.

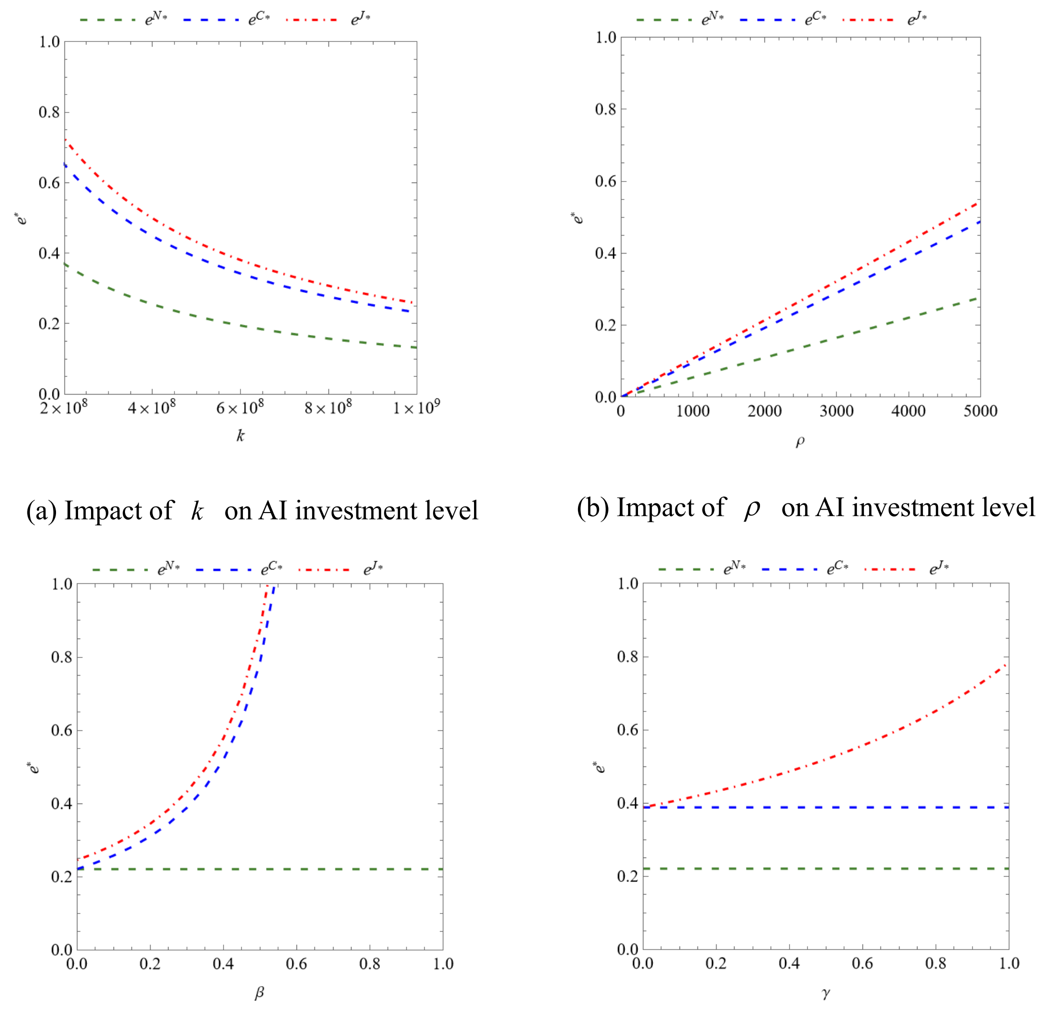
The unit production cost of new power batteries is estimated using battery capacity, average battery prices, and manufacturing-related costs obtained from Bloomberg New Energy Finance and McKinsey & Company [38]. The production costs are first calculated separately for the three representative vehicle models and then averaged to obtain a representative industry benchmark. Accordingly, the baseline production cost is set as $c = 95313$ CNY per unit.

The unit remanufacturing cost is estimated based on the material recovery value of spent lithium-ion batteries reported by Gratz et al. [41]. Considering differences in battery weight among the selected vehicle models, the remanufacturing cost is obtained by deducting the recovered material value from the corresponding production cost. The resulting average remanufacturing cost is calibrated as $c_r = 80746$ CNY per unit.

The unit value of high-quality retired batteries for echelon utilization is calibrated according to the valuation approach proposed by Madlener and Kirmas [42]. Differences in residual battery capacity and processing costs are incorporated for the three representative battery types. Based on the average economic value across these cases, the unit value of high-quality retired batteries is set as $v = 55329$ CNY per unit.

The remaining parameters are adopted from widely used settings in the power battery CLSC literature and calibrated to reflect the characteristics of the market. Informed by Zhang et al. [38], Tang et al. [43], and relevant studies, the baseline parameter values are given by $a = 300000$, $b = 1.6$, $\rho = 7000$, $k = 7.5 \times 10^8$, $s = 0.3$.

5.2. Impacts of different parameters on decision making on level of AI technology investment



(a) Impact of k on AI investment level (b) Impact of ρ on AI investment level

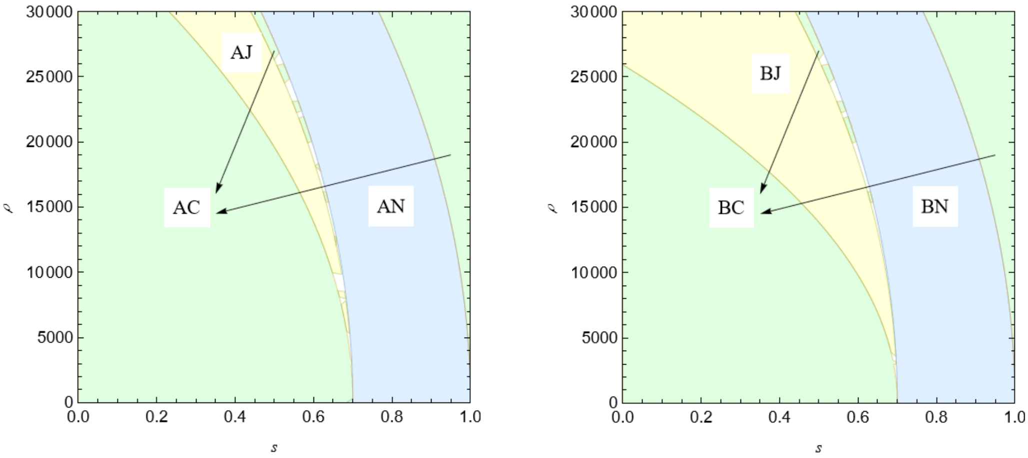
(c) Impact of β on AI investment level (d) Impact of γ on AI investment level

Figure 4. Variation of e with different parameters.

Figure 4 illustrates the AI investment levels under the independent investment scenario, the cost-sharing scenario, and the revenue-cost sharing scenario. As shown in Figure 4(a), AI investment decreases with increasing AI cost across all three scenarios. This occurs because higher per-unit AI costs weaken the supplier's incentive to invest in technology, which is consistent with Corollary 1. Figure 4(b) shows that stronger consumer sensitivity positively affects AI investment. Higher consumer responsiveness increases the market value of AI-driven batteries, thereby motivating the supplier to expand AI deployment, particularly under collaborative scenarios. Figure 4(c) and 4(d) further demonstrate the role of coordination mechanisms. An increase in the cost-sharing ratio results in higher AI investment under both the cost-sharing and revenue-cost sharing scenarios, while AI investment under the revenue-cost sharing scenario remains consistently higher, reflecting the stronger incentives generated by the combination of cost and revenue sharing. Similarly, a higher revenue-sharing ratio significantly promotes AI investment in the revenue-cost sharing scenario but has a negligible impact under the cost-sharing scenario, as revenue sharing directly links AI investment to downstream value realization. Overall, the revenue-cost sharing scenario yields the highest level of AI investment. By simultaneously alleviating the supplier's cost burden and enhancing its ability to capture AI-generated value, this coordination mechanism provides the strongest incentive for AI adoption, thereby supporting the comparative results stated in Proposition 1.

5.3. Impacts of different parameters on wholesale and retail prices

Figure 5 reveals that no single coordination mechanism dominates across all market environments. Instead, the preferred collaboration strategy depends jointly on government subsidy intensity and consumers' acceptance of AI-enabled products. When government subsidies remain relatively high and consumer AI sensitivity is limited, the revenue-cost sharing mechanism provides the strongest price-stabilizing effect by alleviating suppliers' investment pressure while preventing excessive cost pass-through. Under these conditions, the mechanism benefits both upstream and downstream firms by reducing procurement costs and maintaining market competitiveness. As subsidy support gradually declines, however, cost-sharing contracts become more suitable for balancing investment incentives and pricing performance, particularly when consumer demand for AI-enabled products is still developing.



(a) Government subsidy impact on w (b) Government subsidy impact on p

Figure 5. w and p affected by government subsidies.

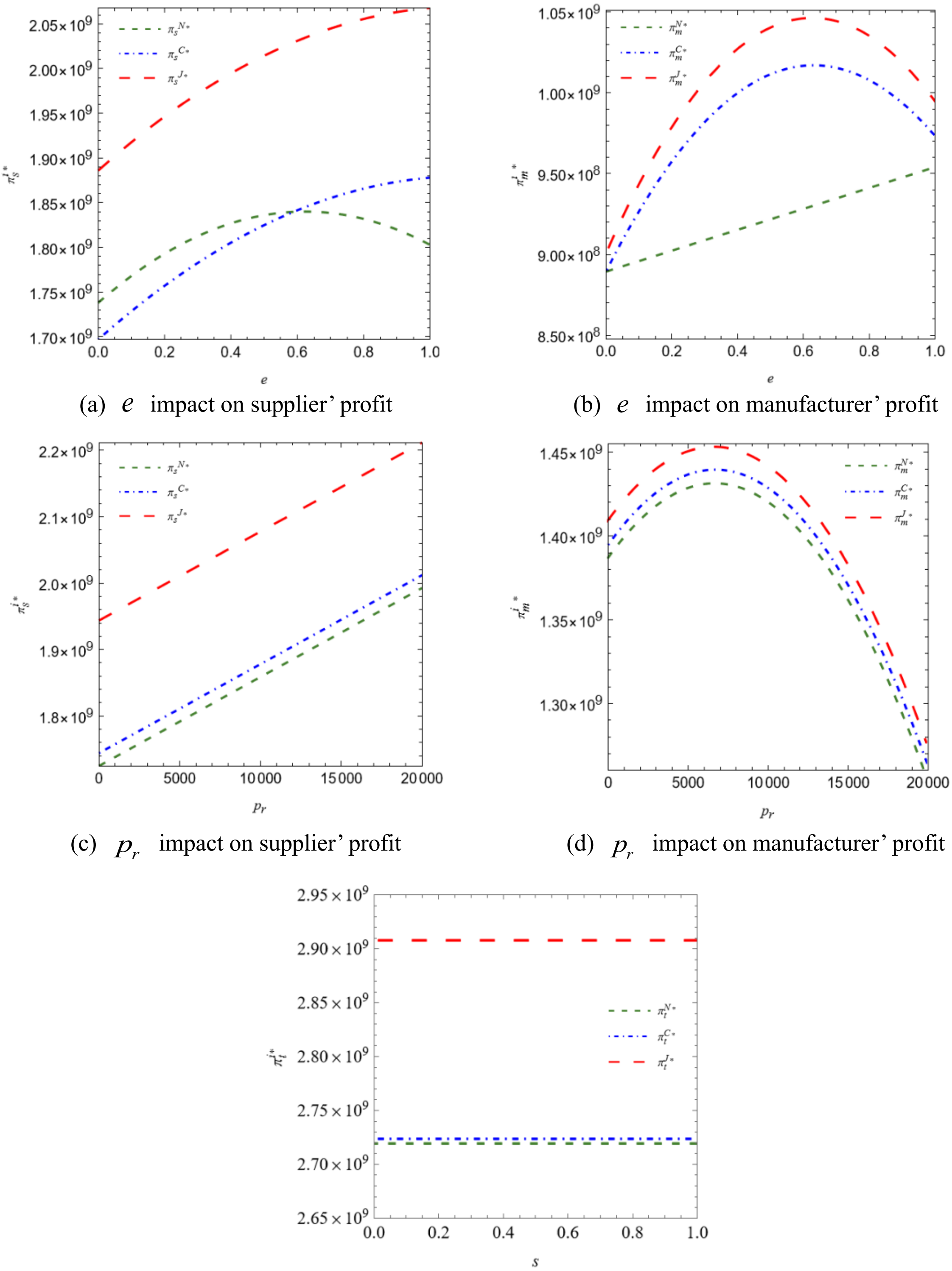
As consumer preference for AI-enabled products continues to increase, the pricing advantage of revenue-cost sharing gradually disappears because suppliers are able to appropriate a larger share of the value created by AI investment through revenue-sharing arrangements. This finding suggests that coordination mechanisms should evolve with market maturity rather than remain unchanged throughout the technology diffusion process. In the early stage of AI adoption, deeper collaboration supported by government subsidies can effectively lower market prices and accelerate technology diffusion. In contrast, as AI becomes widely accepted and subsidy intensity is reduced, supply chain members should dynamically adjust cost-sharing and revenue-sharing arrangements to balance investment incentives with pricing efficiency. These results highlight that effective coordination requires simultaneously considering policy support and market acceptance of AI technologies, rather than relying on a fixed contractual arrangement.

5.4. Impacts of different parameters on the profits of manufacturers and retailers

As shown in Figure 6(a) and 6(b), AI adoption affects firm profitability differently across the three scenarios. For the supplier, profits in the cost-sharing and revenue-cost sharing models steadily increase under higher AI engagement, as shared costs reduce investment burden and improved AI performance stimulates demand. Under the independent investment scenario, supplier profits initially rise but decline at high AI engagement, because marginal AI costs escalate and higher battery prices limit procurement. For the manufacturer, profits in the collaborative scenarios grow at lower levels of AI engagement, but decline at higher levels when procurement costs increase and market demand plateaus. In contrast, under the independent investment scenario, manufacturer profits increase consistently, since the manufacturer bears no AI cost while benefiting from stronger demand and stable procurement prices.

Figure 6(c) and 6(d) illustrate the effects of recycling prices of retired power batteries on firm profits. Supplier profits rise across all scenarios as higher recycling prices enhance residual value, reduce material costs, and improve recovery efficiency, with the largest gains observed under the revenue-cost sharing scenario due to coordinated recycling and shared returns. Manufacturer profits exhibit a non-linear response: moderate recycling prices improve profitability by lowering effective battery costs and enhancing environmental appeal, while excessively high prices increase upstream cost pass-through and reduce consumer willingness to pay. Across all scenarios, manufacturer profit is highest under the revenue-cost sharing scenario, the independent investment scenario yields the lowest profit. The coordination contracts ease the manufacturer' s investment burden and optimize supply chain recycling decisions, generating greater profitability than the decentralized independent investment case.

The impact of government subsidy on total supply chain profit is depicted in Figure 6(e). A comparative analysis shows that increasing subsidy does not significantly enhance overall supply chain profit. Government subsidies fail to dynamically offset rising AI investment and raw material costs, and cost pressures persist along the supply chain. Moreover, subsidy-driven expansion intensifies market competition, which erodes prices and offsets potential gains. Regardless of variations in subsidy levels, the ranking of profits across scenarios remains unchanged: the revenue-cost sharing scenario attains the highest total supply chain profit, followed by the cost-sharing scenario, with the independent investment scenario at the lowest level. This indicates that AI-driven performance improvements and efficiency gains arising from collaborative arrangements are the primary drivers of total supply chain profitability.



(a) e impact on supplier' profit

(b) e impact on manufacturer' profit

(c) p_r impact on supplier' profit

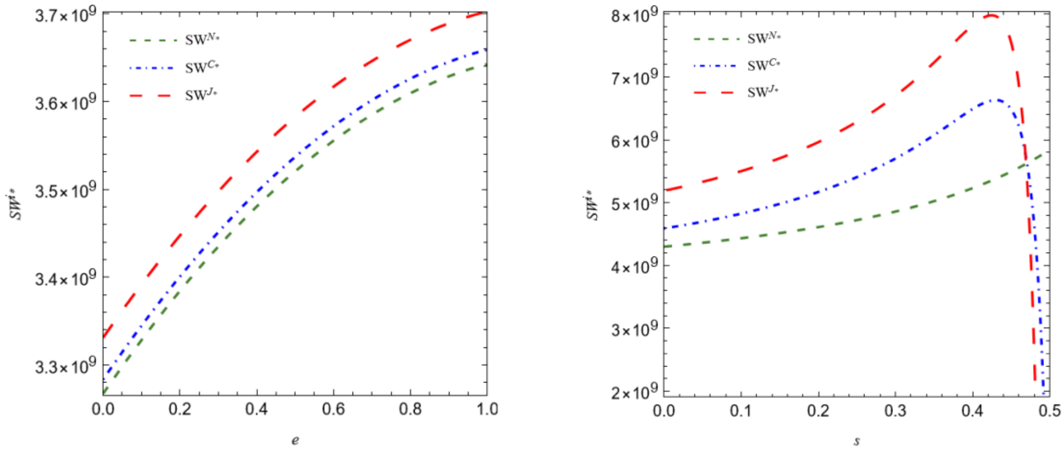
(d) p_r impact on manufacturer' profit

(e) s impact on total supply chain profit

Figure 6. π_s, π_m and π_t affected by different parameters.

5.5. Social welfare analysis

As illustrated in Figure 7(a) and (b), AI investment and government subsidy levels exert differential effects on social welfare across the three scenarios. In all scenarios, social welfare increases with higher AI investment, verifying that AI technology deployment exerts a positive impact on the welfare of the power battery closed-loop supply chain. For a given AI investment level, social welfare under the revenue-cost sharing scenario is consistently the highest, followed by that under the cost-sharing scenario, while the independent AI investment scenario achieves the lowest social welfare. In addition, the welfare gap between the three scenarios gradually expands as AI investment rises, indicating that the marginal welfare contribution of supply chain coordination becomes more significant with higher AI intensity. Under the revenue-cost sharing scenario, the combined cost-sharing and revenue-sharing mechanism effectively internalizes the positive externalities of AI investment. This arrangement not only enhances the supplier's willingness to invest in AI, but also coordinates the pricing and recycling decisions of upstream and downstream members, thereby jointly driving improvements in firm profits, consumer surplus, and ultimately generating the greatest welfare gains. The cost-sharing scenario partially alleviates the supplier's investment pressure and enables a higher AI input level than the independent mode, thus leading to moderate welfare improvements. By contrast, in the independent investment scenario, the supplier bears the full AI investment cost independently, resulting in weaker investment incentives and limited diffusion of AI benefits along the supply chain, which constrains the growth of overall social welfare. When government subsidies are introduced, social welfare in the two collaborative scenarios initially increases but subsequently declines at high subsidy levels. This non-monotonic pattern is driven by excessive AI expansion and output growth, which intensify market competition, compress profits, and increase environmental pressure from overproduction. By comparison, social welfare under the independent investment scenario continues to increase with subsidy intensity, as subsidy effectively reduces the supplier's cost burden without inducing excessive capacity expansion. Overall, these results highlight that coordination mechanisms critically shape how AI investment and government subsidies translate into social welfare outcomes.

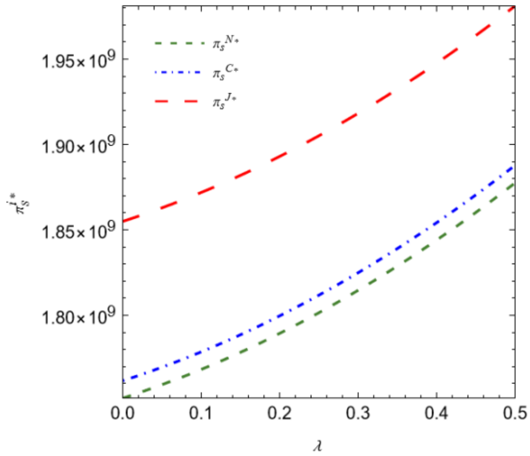


(a) Impact of e on social welfare (b) Impact of s on social welfare

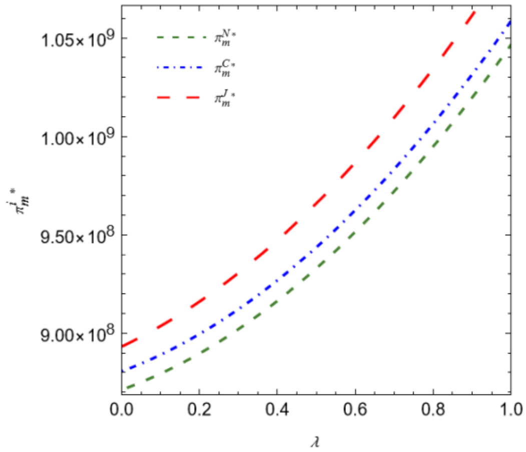
Figure 7. SW^i affected by different parameters.

5.6. Robustness analysis

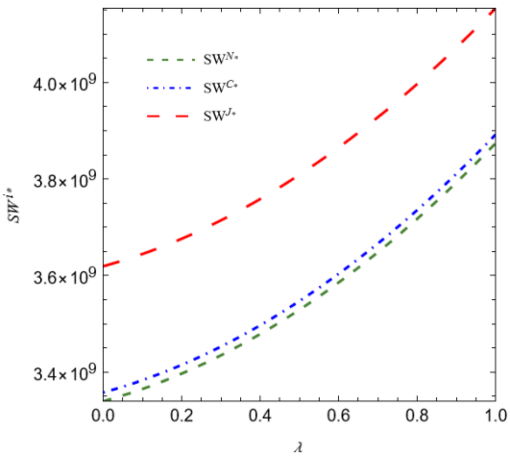
To assess the robustness of the main findings, we vary the proportion of high-quality retired batteries. Figure 8 shows that, although higher values of λ improve the profitability and social welfare of all three coordination mechanisms by increasing the value recovered through cascade utilization, they do not alter the relative performance of the models. The revenue-cost sharing model consistently delivers the highest supplier profit, manufacturer profit, and social welfare, followed by the cost-sharing model and the independent investment model. This finding indicates that the performance gains achieved through coordination are structural rather than parameter-specific. In other words, improvements in battery quality enhance the economic performance of the entire supply chain but do not substitute for the incentive alignment generated by coordination contracts. Therefore, the advantages of coordinated AI investment remain robust across different battery recovery conditions.



(a) λ impact on supplier' profit



(b) λ impact on manufacturer' profit



(c) λ impact on social welfare.

Figure 8. Impact of λ on profits of the CLSC and social welfare.

6. Extensions

6.1. Environmental analysis

The baseline model assumes that unit environmental impacts are exogenously given, implying AI affects environmental performance only through expanding production and recycling scale. To incorporate the direct emission-reduction capability of AI technology, we extend the model by endogenizing the unit environmental intensity of AI-empowered stages as a concave decreasing function of AI investment [20,44]. The revised total environmental impact function is formulated as:

$$E^i = \left[d^i - (1-\lambda)q^i \right]\left(\tau_m - \eta\sqrt{e^i}\right) + (1-\lambda)q^i\left(\tau_r - \eta\sqrt{e^i}\right) + \lambda q^i \tau_t + d^i\left(\tau_c - \eta\sqrt{e^i}\right) + \left(d^i - q^i\right)\tau_u \tag{10}$$

where η represents the AI-enabled marginal emission abatement efficiency, which captures the reduction magnitude of unit environmental intensity per unit of AI investment.

Proposition 6: $E^{N*} < E^{C*} < E^{J*}$, when $\eta > \eta_0$.

Proposition 6 demonstrates that when the AI-enabled marginal emission abatement efficiency exceeds the critical threshold, the total life-cycle environmental impacts of the power battery closed-loop supply chain exhibit a specific ranking, with the independent AI investment mode achieving the lowest environmental impact and the full revenue-cost sharing coordination mode resulting in the highest impact. This counterintuitive result is primarily attributed to the dominance of the scale expansion effect. Specifically, deeper supply chain coordination stimulates greater AI investment and promotes the expansion of production and recycling activities. However, the additional emissions induced by the enlarged operational scale exceed the marginal emission reduction benefits generated by AI-enabled efficiency improvements. Moreover, certain emission sources, such as the unavoidable environmental burdens associated with echelon utilization and consumer disposal behaviors beyond supply chain control, remain difficult to mitigate through AI technologies, further amplifying the environmental differences among coordination modes. These findings indicate that although AI adoption can improve emission efficiency, its environmental benefits may be insufficient to offset scale-induced emission growth under intensive supply chain coordination. Therefore, supply chain collaboration should be carefully designed by considering the balance between operational expansion and environmental performance rather than solely pursuing higher coordination intensity.

6.2. Social welfare

The previous analysis evaluates social welfare under the three decision-making modes based on the classical closed-loop supply chain welfare framework developed by Wu and Zhou [40], which primarily captures the economic benefits generated by supply chain participants. However, the deployment of AI technology in the new energy vehicle industry not only affects firms' operational decisions but also creates broader technological externalities. In practice, governments commonly intervene in technology adoption and industrial development through subsidy policies, implying that a welfare evaluation based solely on market participants' economic outcomes may underestimate the overall social value of AI-enabled closed-loop supply chains.

To address this limitation, this section extends the social welfare framework by incorporating government subsidy decisions into the welfare evaluation system and further examines the optimal subsidy strategy and its welfare implications under different decision-making modes. Following the government subsidy-based welfare evaluation frameworks proposed by Li et al. [45]and Pi et al. [46], the extended social welfare function comprises three components: the total profits of supply chain members, consumer surplus, and government subsidy expenditure. Accordingly, the generalized social welfare function is expressed as follows:

$$SW^i = \pi_s^i + \pi_m^i + CS^i - G^i \tag{11}$$

G^i represents the total government subsidy expenditure under mode *i*.

Proposition7: $SW^{N*} < SW^{C*} < SW^{J*}$, if $0 < \beta < \beta_2, 0 < \gamma < \gamma_2$.

Proposition 7 demonstrates that, after incorporating government subsidy expenditure into the welfare evaluation framework, net social welfare follows the ranking of the independent AI investment model, cost-sharing model, and revenue-cost sharing model, provided that β and γ remain within their feasible ranges. This result arises because the welfare gains generated by enhanced AI adoption and supply chain coordination exceed the additional fiscal burden associated with higher subsidies. In the independent investment model, the supplier bears the entire AI investment cost, leading to insufficient technology adoption and limited improvements in supply chain performance and consumer surplus, despite requiring the lowest subsidy expenditure. The cost-sharing mechanism alleviates investment constraints and stimulates higher AI adoption, thereby generating additional economic benefits that compensate for the increased fiscal cost. The revenue-cost sharing mechanism further strengthens incentive alignment and induces the highest AI investment level, resulting in the largest improvements in supply chain profitability and consumer surplus. Although it requires the highest subsidy expenditure, the resulting economic benefits are sufficient to offset the fiscal burden, making it the most socially desirable coordination mode. This finding highlights that appropriate coordination mechanisms can improve the effectiveness of government subsidies by converting fiscal support into greater social returns.

Corollary 4: $\dfrac{\partial SW^{N*}}{\partial s} > 0, \text{when } s < \dfrac{b-2}{b+6}$.

$\dfrac{\partial SW^{C*}}{\partial s} > 0, \text{when } s < \dfrac{b-6\beta-b\beta-2}{b+6}$. $\dfrac{\partial SW^{J*}}{\partial s} > 0, \text{when } s < \dfrac{b-6\beta-b\beta+4\beta\gamma-2}{b-4\gamma+6}$.

Corollary 4 reveals that the impact of government subsidy intensity on net social welfare exhibits an inverted-U relationship across the three decision-making regimes, with a regime-specific optimal subsidy threshold. Specifically, net social welfare increases with the subsidy rate only when the subsidy level remains below the corresponding threshold. This result reflects the dual role of government subsidies: moderate subsidies reduce the effective cost of AI adoption, stimulate technology investment, and enhance supply chain and consumer benefits; however, excessive subsidies increase fiscal burdens and may induce inefficient expansion beyond the socially optimal level. Once the subsidy rate exceeds the threshold, the marginal fiscal cost and scale-related welfare losses outweigh the additional benefits from AI-driven improvements, resulting in declining net social welfare. Furthermore, the optimal subsidy threshold decreases as supply chain coordination deepens, because cost-sharing and revenue-sharing mechanisms partially internalize AI investment externalities and improve investment efficiency. Therefore, government subsidies and supply chain coordination serve as partially substitutable policy instruments, suggesting that stronger coordination requires more precise and moderate subsidy design to avoid excessive fiscal expenditure and achieve higher social welfare.

6.3. Demand enhancement through AI-specific functionalities

In this section, we examine an extension that explicitly incorporates the distinctive functionalities enabled by AI technologies. AI technologies provide a series of distinctive functionalities and these capabilities improve the transparency, reliability and traceability of battery manufacturing processes, thereby strengthening consumers' confidence in manufactured battery products and generating additional market demand [47]. Following Niu et al. [48] and Sun and Tu [49], we extend the demand function by introducing an AI-enabled functionality spillover coefficient δ, which measures the additional demand created by AI-specific functionalities beyond the conventional demand-enhancing effect of AI investment, $\delta > 0$. Accordingly, the market demand function of the product is:

$$d = a - bp + \rho e + \delta e \tag{12}$$

Since the modified demand function preserves the linear structure of the original model, the analytical procedure remains unchanged. The equilibrium solutions can be obtained following the same backward induction approach.

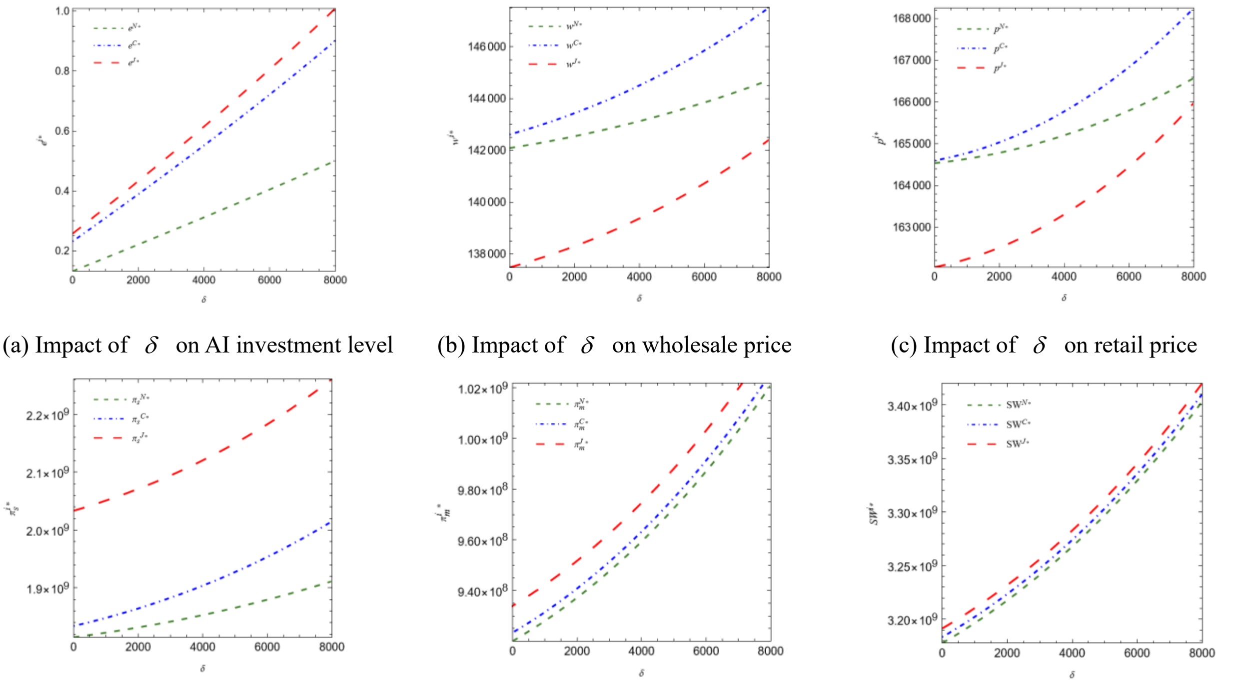
Proposition 8: (1) $e^{N*} < e^{C*} < e^{J*}$.

(2) $\pi_S^{N*} < \pi_S^{C*} < \pi_S^{J*}$.

(3) $\pi_m^{N*} < \pi_m^{C*} < \pi_m^{J*}$, if $0 < \beta < \beta_3, 0 < \gamma < \gamma_3$.

Proposition 8 demonstrates that incorporating AI-enabled functionality into the demand function does not alter the qualitative equilibrium properties of the baseline model. Specifically, the equilibrium ranking of AI investment levels and supplier profits remains identical to that obtained in the main model. This is because AI-enabled functionalities generate an additional demand spillover by enhancing consumers' confidence in product quality and lifecycle transparency. The resulting market expansion uniformly increases the supplier's revenue under all decision structures, thereby preserving the original profit ordering. Overall, the introduction of AI-enabled functionalities affects the absolute magnitude of market demand and profits but does not modify the economic mechanism underlying the equilibrium outcomes.

Based on the data in Section 5, we show the impact of δ on equilibrium decisions, profits, and social welfare in Figure 9. The results show that the AI investment level, wholesale price, retail price, supplier profit, manufacturer profit, and social welfare all increase as δ increases, while their relative rankings remain unchanged throughout the feasible parameter range. This is because the AI-enabled functionality spillover generates additional market demand by strengthening consumers' confidence, thereby expanding the market size under all decision structures. Although the introduction of δ improves the absolute levels of the equilibrium outcomes, it affects all decision structures in the same direction and therefore does not alter the underlying economic mechanisms or the relative equilibrium rankings. The results confirm the robustness of the baseline model and indicate that incorporating AI-enabled functionality spillovers enhances overall supply chain performance without changing the principal managerial insights derived from the original analysis.



(a) Impact of δ on AI investment level (b) Impact of δ on wholesale price (c) Impact of δ on retail price

(d) Impact of δ on supplier's profit (e) Impact of δ on manufacturer's profit (f) Impact of δ on social welfare

Figure 9. Impact of δ on equilibrium decisions, profits, and social welfare.

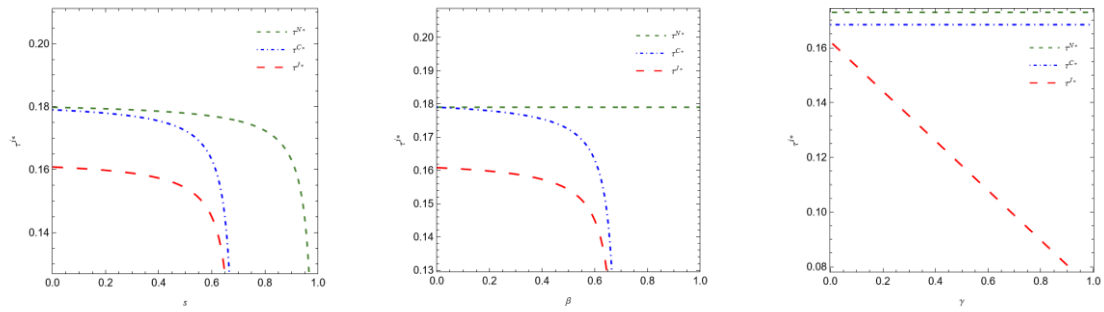
6.4. Analysis of the recycling quantity

In the main model, the recycling quantity is specified as $q = p_r$, which depends solely on the recycling price without explicitly incorporating the physical constraint. Although this reduced-form specification facilitates analytical tractability, it is necessary to verify that the resulting equilibrium solutions remain physically feasible under realistic parameter settings. In this section, we conduct an additional robustness analysis using the parameter settings in Section 5. Specifically, referring to the work of Zhang et al. [37], we assume the optimal recycling rate as:

$$\tau^{i*} = \frac{q^{i*}}{d^{i*}}, i \in \{N, C, J\} \tag{13}$$

and examine its sensitivity to the key parameters. Since $\tau^{i*} < 1$ is equivalent to $q^{i*} < d^{i*}$, the recycling rate provides a measure of whether the sales constraint is satisfied.

Figure 10 presents the corresponding results. Across all coordination modes and the entire parameter space considered, the equilibrium collection rate remains consistently below unity, indicating that the equilibrium recycling quantity never exceeds the corresponding market demand. Overall, these findings confirm the robustness of the baseline model from two perspectives. First, the equilibrium solutions always satisfy the physical constraint $q^{i*} < d^{i*}$, demonstrating that the simplified recycling specification is consistent with the operational characteristics of power battery closed-loop supply chains. Second, government subsidy and stronger supply chain coordination stimulates market demand more rapidly, resulting in a gradual decline in the recycling rate. This observation is consistent with the scale-expansion effect identified in the main analysis and further supports the robustness of the environmental conclusions.



(a) s impact on recycling rate (b) β impact on recycling rate (c) γ impact on recycling rate

Figure 10. Impact of key parameters on τ^{i*}.

7. Conclusion

We consider the power battery supply chain consisting of a power battery supplier and a NEV manufacturer, focusing on how collaboration structures and government subsidies influence AI technology investment. Three models are compared: independent investment, cost-sharing, and revenue-cost sharing. The research explores how to design collaboration mechanisms that drive technological upgrades. We also examine how these mechanisms enhance supply chain coordination. Finally, the study evaluates their impact on economic, environmental, and social outcomes in AI-driven closed-loop supply chains.

7.1. Main findings

AI-enabled intelligent upgrading has become an important approach for improving recycling efficiency and enhancing the full-life-cycle value of power batteries with the rapid growth of new energy vehicles. Existing studies have demonstrated that AI technologies can improve closed-loop supply chain performance through intelligent sorting, predictive analysis, and information sharing [3,13]. Government subsidies are widely adopted to stimulate firms' AI investment and accelerate digital transformation, but subsidy-based policies require continuous fiscal support and may impose long-term financial burdens on governments [17,18]. Moreover, due to the spillover effects of AI technologies, individual firms may be unable to fully capture the benefits of their investment, resulting in insufficient investment incentives [16]. Supply chain coordination contracts provide a market-oriented approach to alleviate such investment inefficiencies by improving cost and benefit allocation among participants. However, how government subsidies interact with coordination mechanisms to promote AI adoption in power battery closed-loop supply chains remains unclear.

In this paper, we consider a two-echelon power battery closed-loop supply chain consisting of a battery supplier and a new energy vehicle manufacturer and develop a Stackelberg game framework. Three decision models are established, including independent AI investment, cost-sharing coordination, and revenue-cost sharing coordination. We examine the impacts of AI investment, contract parameters, and subsidy policies on supply chain decisions and compare the three modes from the perspectives of AI investment, pricing decisions, profitability, environmental performance, and social welfare. The main findings are summarized as follows:

(1) Consistent with previous studies on technology coordination in CLSCs, both coordinated modes stimulate higher AI investment than the independent mode, confirming that coordination alleviates suppliers' investment constraints. However, this study further shows that revenue-cost sharing provides substantially stronger investment incentives than pure cost sharing. Unlike conventional technologies, AI generates value spillovers throughout the entire battery lifecycle. By coordinating both cost allocation and revenue distribution, the revenue-cost sharing contract enables suppliers to capture a larger proportion of the value created by AI, thereby producing stronger investment incentives than cost-side coordination alone.

(2) The finding that revenue-cost sharing yields the lowest wholesale and retail prices under moderate subsidy levels is consistent with existing evidence that revenue-inclusive contracts mitigate double marginalization. In contrast, pure cost sharing results in higher prices than the independent mode, differing from the conventional view that cost-sharing coordination always reduces prices. This occurs because cost sharing alleviates suppliers' investment burden without constraining their pricing incentives, allowing both upstream and downstream firms to pass part of the investment cost to consumers. The results suggest that cost sharing alone may not generate consumer price benefits unless accompanied by appropriate revenue-side coordination.

(3) We find that supplier profitability is consistently enhanced under both coordinated modes, corroborating previous evidence from the CLSC literature. However, unlike studies assuming universal improvements, manufacturer profits increase only when the cost-sharing and revenue-sharing ratios remain within appropriate ranges. Excessive sharing transfers a disproportionate share of coordination gains to the supplier, offsetting the manufacturer's benefits from demand expansion. This finding highlights that technology-oriented coordination improves total supply chain performance but does not necessarily ensure balanced profit allocation among members.

(4) Our findings are consistent with prior studies in showing that moderate government subsidies enhance social welfare by strengthening the economic benefits. Nevertheless, two findings extend the existing literature. First, social welfare exhibits an inverted-U relationship with subsidy intensity, indicating that excessive subsidies reduce overall welfare. Second, stronger coordination leads to higher total lifecycle environmental impacts because AI-induced market expansion outweighs the environmental gains from improved operational efficiency. These results reveal an important trade-off between AI-driven coordination and sustainability, suggesting that technological upgrading does not necessarily translate into environmental improvements.

7.2. Managerial implications

Our findings provide several managerial implications for AI-enabled power battery CLSC under government subsidy policies.

First, for power battery suppliers, collaborative AI investment with downstream manufacturers is preferable to independent technology deployment. Cost-sharing and revenue-cost sharing contracts can internalize the positive externalities of AI-enabled operational improvements, alleviate the upfront investment burden, and strengthen incentives for AI adoption. Under government subsidy schemes, deeper cost-revenue alignment with manufacturers can further amplify the marginal returns of AI investment and ultimately enhance suppliers' profitability.

Second, manufacturers should actively participate in collaborative investment and periodically adjust cost-sharing and revenue-sharing arrangements as market and policy conditions evolve. Well-designed coordination contracts help elevate the overall AI investment level of the supply chain and expand market demand for products, while supporting a balanced distribution of benefits across supply chain members.

Finally, governments should prioritize subsidy effectiveness rather than subsidy intensity. Moderate subsidies combined with supply chain coordination generate stronger incentives for AI adoption and higher social welfare than excessively generous subsidies. However, AI-driven coordination entails a clear economic-environmental trade-off. While it significantly bolsters AI investment incentives, supply chain profitability and overall social welfare, deeper coordination also increases the environmental impact of power batteries through the scale-expansion effect, and higher subsidy intensity will further magnify this environmental pressure. Accordingly, when designing AI-targeted subsidy policies, governments must fully consider the balance between economic efficiency and environmental sustainability. In parallel, subsidy intensity should be maintained within an appropriate range matched to the supply chain coordination mode, to promote the social welfare gains from AI technology upgrading.

These implications are also relevant to other regions. For example, the European Union has introduced targeted support policies for technological upgrading and intelligent operation in the battery industry to facilitate the circular development of power battery supply chains. Our findings indicate that technology-support policies are most effective when combined with supply chain coordination mechanisms rather than relying solely on stronger financial incentives.

7.3. Future research

This study has several limitations that provide opportunities for future research. First, the analysis considers a two-echelon CLSC consisting of a battery supplier and an NEV manufacturer; future studies could extend the framework to include third-party recyclers or platform-based recycling systems. Second, this study treats supply chain members as homogeneous agents, whereas firm heterogeneity is pervasive in industrial practice. Heterogeneity may moderate the marginal incentive effect of government subsidies on AI investment, result in divergent optimal cost-sharing and revenue-sharing parameters, and alter the relative economic and environmental performance of different coordination mechanisms. Future work could incorporate firm heterogeneity into the game-theoretic framework, explore targeted subsidy schemes and differentiated coordination contracts, and investigate how inter-firm differences shape equilibrium decisions and system performance in power battery CLSCs. Third, government subsidies are modeled as exogenous policy parameters, whereas future work could investigate endogenous government decision-making or combine subsidies with carbon trading and extended producer responsibility policies. Finally, future research may incorporate demand uncertainty, AI learning effects, or dynamic technology evolution to further explore long-term coordination strategies for sustainable battery recycling systems.

Author contributions

Both authors contributed equally to this work.

Use of Generative-AI tools declaration

The authors declare that they did not utilize any artificial intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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