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Driving Net-Zero Circularity: Business Model Selection and AI-Enhanced Echelon Utilization in Closed-Loop EV Battery Supply Chains

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The realization of net-zero manufacturing in electric vehicles (EVs) relies on effective battery reuse and recycling. This paper analyzes how business model selection, direct selling (BS) or battery leasing (BL), together with artificial intelligence (AI)-enhanced sorting, affects pricing, demand, and profitability in closed-loop EV battery supply chains. A Stackelberg game compares three settings: no echelon utilization, traditional echelon utilization, and AI-supported echelon utilization. The analysis shows that under BS, the forward and reverse channels are separated, so the new EV price remains unchanged. Under BL, the channels are integrated, allowing residual battery value to lower consumers' access costs. We further derive threshold conditions for adopting echelon utilization and AI, which depend on reuse value and AI cost but not on the business model. The comparative profitability of BS and BL is determined by the price sensitivity of recycling volume to the recycling price under BS: BL is more advantageous when this sensitivity is low, while BS yields higher profitability when it is high. These results provide theoretical insights into how business model choice and AI-enhanced echelon utilization jointly shape pricing, value creation, and profit allocation in the EV battery industry.

Keywords: EV battery recycling; Closed-loop supply chain; Artificial intelligence; Echelon utilization; Battery leasing.

1. Introduction

Mobile electrification has dramatically accelerated the global adoption of EVs, resulting in a large number of retired power batteries (RPBs). When the capacity

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of these batteries drops to about 80% of the initial value, they are usually retired. However, at this point, they still have significant potential for second-life applications. RPBs can be reused for stationary energy storage, grid balancing, and integration with renewable energy systems (Zhang *et al.*, 2025). This process, called echelon utilization, can provide significant environmental and economic benefits. The success of this reuse strategy largely depends on the business model of battery deployment.

At present, there are two main business models for power batteries: direct selling (BS) and battery leasing (BL). In the BS model, the battery is sold with the vehicle, and the ownership is transferred to the consumer at the time of purchase. When the battery reaches the end of its life, it will be recycled through formal recycling channels. For example, China Tower purchased these RPBs from manufacturers such as BYD and BAIC and reused them in telecom base stations (IDTechEx, 2025). In contrast, under the BL model, battery ownership remains with the supplier, while users obtain flexible usage rights through periodic payments. This arrangement reduces upfront costs for consumers and facilitates a more predictable battery recycling process (Xu *et al.*, 2026). Companies such as NIO have pioneered battery leasing services in China, with their success primarily attributed to a vertically integrated business model that addresses challenges in compatibility, standardization, and automaker involvement (Shi and Hu, 2024).

Both models have strong potential but also face key challenges. In the BS model, it is difficult to predict the value and quality of RPBs, leading to distorted pricing and low reuse rates. The BL model, by contrast, gives providers full visibility into battery life cycles, but this requires heavy investment in monitoring systems and battery-swapping infrastructure. Furthermore, the inherent diversity of RPBs and variability in capacity degradation complicate accurate classification and pricing, thereby hindering effective implementation of BL models.

Against this backdrop, Artificial Intelligence (AI) is becoming a driver of battery reuse (Shen *et al.*, 2025). AI-driven diagnostic technologies improve battery state-of-health (SoH) assessment, reduce misclassification, and enhance operational efficiency, enabling personalized pricing and contract design. Companies such as Smartville and Redwood Materials have implemented AI-driven diagnostic and sorting technologies to assess battery SoH and optimize reuse pathways, significantly reducing evaluation time and enabling large-scale second-life applications (Smartville Inc., 2024; Chacon *et al.*, 2026). Despite this, existing studies on RPB reuse have largely treated AI as a background assumption rather than examining how it interacts with business model choice to shape pricing outcomes in practice. These interactions are crucial for maximizing economic and environmental value in closed-loop supply chains (CLSCs). We therefore examine the following research questions:
RQ1: What are the differences between BS and BL models in pricing strategies, and what operating factors lead to these differences?
RQ2: How does AI affect the pricing under BS and BL, and how does it affect profitability and adoption threshold?

RQ3: What strategic insights can guide stakeholders to choose business models and AI investments to optimize CLSC performance?

To address these questions, we construct CLSC models in which an upstream battery supplier interacts with a downstream EV manufacturer under two business models. Using a game-theoretic approach, we characterize equilibrium pricing, quantity, and recycling decisions under three operational settings (no echelon utilization, traditional echelon utilization, and AI-enabled echelon utilization) for each business model. We then derive conditions under which echelon utilization and AI-based sorting are economically attractive, expressed in terms of the unit reuse value of RPBs and the AI service fee, and show that these thresholds are independent of the chosen business model. Our work shows that BS and BL transmit residual battery value to the market in different ways: through recycling prices under BS and through access prices under BL. This difference shapes members' profitability. In addition, we investigate how AI reliability, sorting and disposal costs, and demand sensitivity affect the equilibrium outcomes. We also find that when consumers pay more attention to recycling prices, the BS model earns more profit than the BL model. Our result shows how crucial it is for firms to respond to changes in the reverse channel when selecting a business model.

The structure of this paper is as follows: Section 2 reviews related literature. Section 3 describes the model setup. Sections 4 and 5 study the BS and BL models, respectively. Section 6 provides a comparative analysis. Section 7 presents some numerical results. Section 8 concludes with managerial insights and possible directions for future research. All proofs are in the Appendix.

2. Literature Review

Our work relates to three streams of literature: CLSCs for power batteries, battery leasing strategies, and the adoption of AI technology.

2.1. *CLSCs for power batteries*

Researchers have examined pricing decisions under the CLSC for RPBs very well. For instance, Liu *et al.* (2021b) introduced a dual-channel CLSC model and found that when manufacturing costs for new products rise, demand for remanufactured products also rises. They also observed that higher retail costs prompt companies to lower prices to maintain demand. Later, Shu *et al.* (2025) studied pricing and collection strategies over two periods and found that more intense recycling competition raises both the collection price and the price of new products. However, most of these models assume that consumers always own the battery, which may not hold true as vehicle-battery separation becomes more common.

Technology investment has become an increasingly prominent topic in CLSC research. Rahmani *et al.* (2021) compared individual and collective reuse systems and found that collective solutions performed better economically and environmentally. Similarly, Qian *et al.* (2025) demonstrated that recycling process innovation and product innovation can complement each other between battery suppliers and EV manufacturers. Although there has been progress, investment in technology for echelon utilization is still limited, and most current models overlook sorting accuracy, which is important for promoting second-life applications. Notably, the role of AI in improving sorting quality and its impact on business model choices has received little attention in the literature.

Another key issue is the uncertainty in the quality of RPBs. Liu *et al.* (2021a) emphasized that uncertainty in remaining capacity diminishes overall supply chain performance. In contrast, **?** highlighted the impact of production cost and battery quality on the results of the second-life market. However, these studies mainly regard battery quality as an exogenous factor and do not explore how the application of sorting technology or AI adoption can actively increase the proportion of high-quality RPBs entering the reverse supply chain. This gap limits their ability to capture the role of upstream sorting decisions in determining downstream echelon utilization outcomes.

Based on the above literature, we develop a unified CLSC framework that incorporates sorting errors and their economic impact into echelon utilization. By comparing BS and BL, we show how business model choice shapes the embedding of reverse-channel value in pricing decisions.

2.2. *Battery leasing strategies*

BL allows consumers to use batteries through lease contracts instead of buying them directly. Using a two-stage game model, Lim *et al.* (2015) found that the BL model could reduce consumers' concerns about the resale value of EVs, and profitability largely depended on the company's pricing and operational decisions.

Regarding the choice of business model, Hildebrandt *et al.* (2016) developed a dynamic battery life-cycle model and emphasized the importance of incentive mechanisms and real-time monitoring. On this basis, Shi and Hu (2024) compared flexible leases and fixed-lease contracts and found that the contract structure significantly impacted welfare and sustainability outcomes. Recent research by Yuan and Wu (2025) examined competition between BS and BL in the forward supply chain, demonstrating that the attractiveness of BL declines as consumer preference for EVs decreases or the battery-to-vehicle value ratio falls. Although their framework utilized a comparable comparative game structure, it focused solely on the forward channel and did not address battery recycling and reuse. In contrast, this study clearly models the decision-making process in the reverse channel and explores how the residual value of batteries and AI-enabled sorting technology jointly affect the pricing and profitability under the two models.

In recent years, researchers have increasingly discussed pricing strategies in BL mode. For example, Hu *et al.* (2023) derived optimal pricing for pay-per-use and subscription models, incorporating battery degradation and consumer time sensitivity. Furthermore, policy factors such as carbon trading and recycling subsidies may influence lease pricing (He *et al.*, 2025). However, few studies have explored the integration of recycling and second-life value into BL pricing.

This study addresses this gap by incorporating recycling and echelon utilization into the BL framework and analyzing how reverse-channel value informs optimal pricing decisions.

2.3. *The adoption of AI technology*

Recent studies emphasize the role of AI in sustainable and circular supply chains. The study of Yang *et al.* (2022) showed that dynamic pricing and AI-supported information disclosure could support sustainability-oriented decision-making. Aldrighetti *et al.* (2023) found that real-time data sharing, forecasting, and adaptive control could significantly improve the performance of the CLSC. In the environmentally friendly supply chain, Yang *et al.* (2025) further showed that the incentives for adopting AI largely depended on consumers' environmental preferences and technology costs.

AI has also been widely used in recycling operations to improve efficiency. Wang (2022) pointed out that AI could improve sustainable operations and recycling platform management. For EV manufacturers, the decision of whether to invest in research and development has become increasingly complex (Yao *et al.*, 2023). In battery reuse, Tao *et al.* (2024) developed a generative learning method to estimate RPB SoH, addressing data scarcity. Niu *et al.* (2025) further showed that in competitive recycling, AI-based quality control markedly improves sorting accuracy.

To address these gaps, we focus on three main issues. First, most current CLSC models for power batteries do not connect ownership structure and business model choices with echelon utilization and sorting errors. We propose a unified framework that brings together BS and BL, and considers how sorting accuracy affects the economics of battery reuse. Second, while earlier studies on BL have looked at contract design, pricing, and user risk, they often overlook how to include recycling and second-life value in BL pricing. In our work, we have included recycling and echelon utilization in the leasing decision process. Third, although AI is often seen as important for sustainable and circular supply chains, most research treats it as an outside efficiency tool instead of a core part of CLSC design. We integrate AI-based sorting as a core element and demonstrate how it informs business model selection, reverse-channel value, and motivation for AI applications.

3. Model Setup

We consider a CLSC with a battery supplier (denoted by s) and an EV manufacturer (denoted by m). In practice, leading battery suppliers (e.g., CATL) typically have strong market power, so we model their interaction as a Stackelberg game with the supplier as the leader. The supplier produces batteries at a unit cost of c_n and sells them to the EV manufacturer at a wholesale price w. The EV manufacturer (e.g., BYD, NIO Inc.) produces vehicle bodies. Following Liu and Zhang (2013), we normalize the vehicle-body production cost to zero, a standard assumption in the CLSC literature that does not affect the equilibrium results.

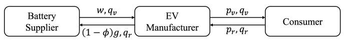
We assume that all RPBs will eventually undergo material recycling, resulting in a net value of g. The net value reflects the cost savings from using recycled materials to replace virgin materials. To ensure that the cost of material recycling does not exceed the unit cost of producing batteries entirely with native materials while providing economic benefits, we set $0 < g < c_n$. Following Kong *et al.* (2023), the recovery value is allocated between the EV manufacturer and the battery supplier at rates ϕ (where $0 < \phi < 1$) and $1 - \phi$, respectively. This contract structure is widely used in recycling collaborations due to its simplicity.

A fraction $\beta \in (0, 1)$ of high-quality RPBs can be reused through echelon utilization, yielding an additional value k. The EV manufacturer sorts RPBs with a baseline accuracy $\alpha \in (0, 1)$, meaning that each battery type is correctly classified with probability α and misclassified with probability $1 - \alpha$. The sorting process incurs a unit cost of c_s. If a low-quality battery is misclassified as high-quality, it will incur an additional processing cost c_e when returned to the recycling center. A high-quality battery misclassified as low-quality loses its echelon utilization value but can still be sent to material recovery at no extra cost.

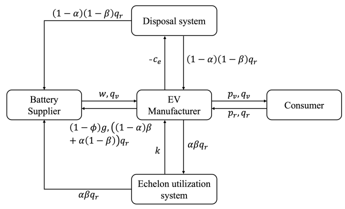
AI improves the sorting process in two ways. First, it improves sorting accuracy. We model AI reliability as $\rho \in (0, 1)$, which increases baseline accuracy to $\alpha_A = \alpha + \rho(1 - \alpha)$. Higher ρ reduces misclassification errors, decreasing the proportion of low-quality RPBs incorrectly routed to echelon utilization and increasing that of high-quality RPBs correctly identified for reuse. Second, AI reduces operational costs: the unit sorting cost decreases from c_s to $(1 - \rho\sigma)c_s$, where $\sigma \in (0, 1)$ denotes the maximum cost reduction achievable through AI-assisted automation.

The manufacturer pays a per-unit fee f to access the AI system. Since f offsets part of the reverse-channel gains, the manufacturer only adopts AI when the net benefit is positive. This gives rise to three scenarios: NN (no echelon utilization), EN (traditional echelon utilization), and EA (AI-enabled echelon utilization), respectively.

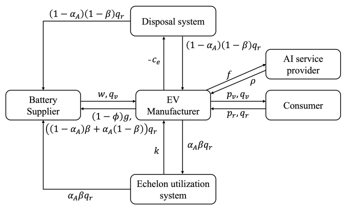
At the same time, the EV manufacturer may operate under either the BS or the BL model. In the BS model, the manufacturer installs batteries into EVs and sells the complete vehicle at price p_v. The demand function is linear: $q_v^{BS} = a - b\,p_v^{BS}$. In this context, a represents market potential, while $b > 0$ quantifies price sensitivity. The analysis examines an interior equilibrium characterized by strictly positive prices and quantities, a condition that necessitates a sufficiently large market size. Consistent with Li *et al.* (2023), the EV manufacturer is responsible for collecting RPBs. The recycling quantity is expressed as a linear function of the recycling price: $q_r^{BS} = R + \theta p_r^{BS}$, where $\theta > 0$ reflects consumer responsiveness. For simplicity, we set $R = 0$, resulting in $q_r^{BS} = \theta p_r^{BS}$. The analysis is further confined to interior equilibria that satisfy $q_r \leq q_v$. Fig. 1 presents the three BS scenarios.



(a) Model BS-NN



(b) Model BS-EN



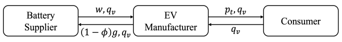
(c) Model BS-EA

Fig. 1. Three CLSC structures under the BS model.

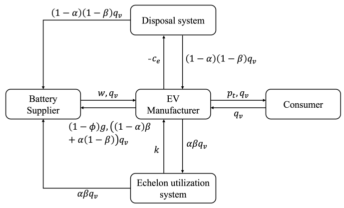
In BL mode, the EV manufacturer separates the battery from the body. Instead of buying the battery, consumers rent it by making regular payments while still owning the car. This arrangement transfers the ownership of the battery and its disposal responsibility after scrapping back to the EV manufacturer. When deciding, consumers focus on the total cost of using the vehicle, including the body price plus the battery rental cost. This assumption is consistent with consumer behavior observed in the EV rental market (e.g., NIO in China and Gogoro in Taiwan), where consumers evaluate electric vehicles primarily based on total cost of use rather than asset ownership.

Therefore, we define the bundled access price p_t as the decision-making variable of the manufacturer, which represents the total cost borne by consumers. The corresponding demand function is $q_v^{BL} = a - bp_t^{BL}$. Following Yuan and Wu (2025), this analysis assumes homogeneous consumers who do not prefer battery ownership, so that purchasing decisions are determined solely by total access cost. While this abstracts away from heterogeneous ownership preferences, it facilitates a tractable and internally consistent comparison of the BS and BL models by isolating the effect of business model structure on pricing and profitability.

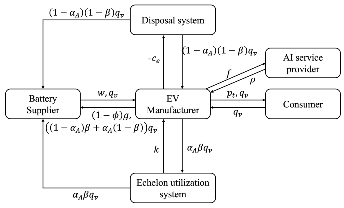
A key operational feature of the BL model is that battery returns are governed by contract rather than price incentives. We assume all leased batteries are contractually recovered at the end of their life, so returns coincide with sales: $q_r^{BL} = q_v^{BL}$. This eliminates the need for a separate recycling price, unlike the BS model, where the manufacturer must set p_r to incentivize voluntary returns. Fig. 2 illustrates the corresponding BL scenarios.



(a) Model BL-NN



(b) Model BL-EN



(c) Model BL-EA

Fig. 2. Three CLSC structures under the BL model.

Table 1 summarizes the notation used in this paper.

Table 1. Parameters and descriptions.

Symbol	Description
Decision Variables	
w	Wholesale price from battery supplier to EV manufacturer
p_t	Bundled access price faced by consumers under the BL model
p_v	Retail price of EVs set by the EV manufacturer
p_r	Recycling price paid by the EV manufacturer to consumers under the BS model
Parameters	
a	Potential market size
b	Consumer price sensitivity ($b > 0$)
θ	Sensitivity of recycling volume to recycling price ($\theta > 0$)
β	Proportion of high-quality RPBs ($0 < \beta < 1$)
α, α_A	Baseline and AI-enhanced sorting accuracy, $\alpha_A = \alpha + \rho(1-\alpha)$
ρ	AI technology reliability ($0 < \rho < 1$)
ϕ	EV manufacturer's share of material recovery value ($0 < \phi < 1$)
σ	Maximum AI cost reduction potential ($0 < \sigma < 1$)
g	Unit net value from material recovery
k	Unit value from echelon utilization
f	Per-unit AI service fee
c_n	Unit production cost of a new battery
c_s	Unit sorting cost
c_e	Unit misclassification handling cost
q_v	Sales quantity of EVs
q_r	Recycling quantity of RPBs
Π_i^{z-j}	Profit of member $i \in \{s, m\}$ in scenario $j \in \{NN, EN, EA\}$ under mode $z \in \{BS, BL\}$

Note: Superscript $*$ denotes the equilibrium value.

4. Model analysis in direct selling (BS)

In this section, we analyze the BS model using a Stackelberg game, where the battery supplier (leader) sets the wholesale price w, and the EV manufacturer (follower) chooses the retail price p_v and recycling price p_r (Savaskan *et al.*, 2004). Throughout the paper, superscript $*$ denotes the equilibrium values for decision variables and profits.

4.1. *No echelon utilization (model BS-NN)*

In this benchmark scenario, the EV manufacturer does not engage in echelon utilization. The profit functions of the battery supplier and the EV manufacturer are given in Eqs. (1) and (2).

$$\max_{\{w\}} \Pi_s^{BS\text{-}NN} = (w - c_n)\, q_v + (1-\phi)\, g\, q_r \tag{1}$$

$$\max_{\{p_v, p_r\}} \Pi_m^{BS\text{-}NN} = (p_v - w)\, q_v + (\phi\, g - p_r)\, q_r \tag{2}$$

We solve the Stackelberg game by backward induction, consistent with the standard solution concept for sequential-move games. The equilibrium outcomes are summarized in Table 2.

Table 2. BS – Equilibrium results for scenarios $j \in \{NN, EN, EA\}$.

	NN	EN	EA
w^{j*}	$\frac{a+bc_n}{2b}$	$\frac{a+bc_n}{2b}$	$\frac{a+bc_n}{2b}$
p_v^{j*}	$\frac{3a+bc_n}{4b}$	$\frac{3a+bc_n}{4b}$	$\frac{3a+bc_n}{4b}$
p_r^{j*}	$\frac{\phi g}{2}$	$\frac{\phi g+\alpha\beta k-(1-\alpha)(1-\beta)c_e-c_s}{2}$	$\frac{\phi g+\alpha_A\beta k-(1-\beta)(1-\alpha_A)c_e-(1-\rho\sigma)c_s-f}{2}$
q_v^{j*}	$\frac{a-bc_n}{4}$	$\frac{a-bc_n}{4}$	$\frac{a-bc_n}{4}$
q_r^{j*}	$\frac{\theta\phi g}{2}$	$\frac{\theta\left[\phi g+\alpha\beta k-(1-\alpha)(1-\beta)c_e-c_s\right]}{2}$	$\frac{\theta\left[\phi g+\alpha_A\beta k-(1-\beta)(1-\alpha_A)c_e-(1-\rho\sigma)c_s-f\right]}{2}$
Π_s^{j*}	$\frac{(a-bc_n)^2+4b\theta\phi(1-\phi)g^2}{8b}$	$\frac{(a-bc_n)^2+4b\theta(1-\phi)\left[\phi g+\alpha\beta k-(1-\alpha)(1-\beta)c_e-c_s\right]g}{8b}$	$\frac{(a-bc_n)^2+4b\theta(1-\phi)\left[\phi g+\alpha_A\beta k-(1-\beta)(1-\alpha_A)c_e-(1-\rho\sigma)c_s-f\right]g}{8b}$
Π_m^{j*}	$\frac{(a-bc_n)^2+4b\theta\phi^2g^2}{16b}$	$\frac{(a-bc_n)^2+4b\theta\left[\phi g+\alpha\beta k-(1-\alpha)(1-\beta)c_e-c_s\right]^2}{16b}$	$\frac{(a-bc_n)^2+4b\theta\left[\phi g+\alpha_A\beta k-(1-\beta)(1-\alpha_A)c_e-(1-\rho\sigma)c_s-f\right]^2}{16b}$

Based on Table 2, we examine how the parameters b and g influence the battery wholesale price $w^{BS\text{-}NN*}$, the EV retail price $p_v^{BS\text{-}NN*}$, the battery recycling price $p_r^{BS\text{-}NN*}$, and members' profits $\Pi_i^{BS\text{-}NN*}$ (for $i \in \{s, m\}$), as stated in Lemma 1.

Lemma 1. *In model BS-NN,*

(a) The optimal wholesale price $w^{BS\text{-}NN*}$ and retail price $p_v^{BS\text{-}NN*}$ are decreasing in b and invariant with respect to g.
(b) The optimal battery recycling price $p_r^{BS\text{-}NN*}$ is invariant with respect to b and increasing in g.
(c) The optimal profits $\Pi_i^{BS\text{-}NN*}$ are decreasing in b and increasing in g.

A higher b means consumers are more price-sensitive. Lemma 1(a) demonstrates that increased consumer price sensitivity leads to a reduction in market size, which in turn requires the battery supplier to decrease the wholesale price to sustain positive demand. Combined with Lemma 1(b), this implies that, under the BS model, pricing decisions in the new-vehicle and recycling markets are independent. A higher residual value g makes recycling more attractive, so the EV manufacturer raises the recycling price to attract more RPBs and capture more reuse value. Lemma 1(c) further clarifies that an increase in price sensitivity b reduces profits by compressing margins in the primary market. In contrast, a higher residual value g enhances profitability by strengthening the appeal of recycling activities.

4.2. *Traditional echelon utilization (model $BS-EN$)*

When the EV manufacturer engages in echelon utilization without adopting AI, the profit functions of the two parties are given in Eqs. (3) and (4).

$$\max_{\{w\}} \Pi_s^{BS\text{-}EN} = (w - c_n)\, q_v + (1-\phi)\, g\, q_r \tag{3}$$

$$\max_{\{p_v, p_r\}} \Pi_m^{BS\text{-}EN} = (p_v - w)\, q_v + \Big[\phi\, g + \alpha\beta k - (1-\alpha)(1-\beta)c_e - c_s - p_r\Big]\, q_r \tag{4}$$

Applying backward induction yields the equilibrium outcomes in Table 2.

Based on Table 2, we examine how the echelon utilization parameters k, α, c_e, and c_s influence the battery wholesale price $w^{BS\text{-}EN*}$, the EV retail price $p_v^{BS\text{-}EN*}$, the battery recycling price $p_r^{BS\text{-}EN*}$, and members' profits $\Pi_i^{BS\text{-}EN*}$ (for $i \in \{s, m\}$), as presented in Lemma 2.

Lemma 2. *In model BS-EN,*

(a) Both $w^{BS\text{-}EN*}$ and $p_v^{BS\text{-}EN*}$ are invariant with respect to the echelon utilization parameters k, α, c_e, and c_s.
(b) The recycling price $p_r^{BS\text{-}EN*}$ and the profits $\Pi_i^{BS\text{-}EN*}$ are increasing in α and k, and decreasing in c_e and c_s.

Lemma 2(a) indicates that equilibrium wholesale and retail prices are determined by conditions in the new-vehicle market. Echelon utilization does not influence wholesale or retail prices. Lemma 2(b) demonstrates that increased sorting accuracy

α and higher echelon utilization value k lead to higher recycling prices and greater profits for both firms. Conversely, increased disposal and sorting costs diminish these outcomes. These effects occur exclusively through the recycling channel and do not affect the equilibrium in the primary vehicle market.

4.3. *AI-enabled echelon utilization (model $BS - EA$)*

When the EV manufacturer adopts AI to improve sorting accuracy and reduce sorting cost, the profit functions for both parties are given by Eqs. (5) and (6).

$$\max_{\{w\}} \Pi_s^{BS\text{-}EA} = (w - c_n)\, q_v + (1-\phi) g\, q_r \tag{5}$$

$$\begin{aligned}\max_{\{p_v, p_r\}} \Pi_m^{BS\text{-}EA} = (p_v - w)\, q_v + \Big[&\phi g + \alpha_A \beta k - (1-\beta)(1-\alpha_A)\, c_e \\ &- (1-\rho\sigma) c_s - f - p_r\Big] q_r\end{aligned} \tag{6}$$

Applying backward induction yields the equilibrium outcomes in Table 2.

Based on Table 2, we examine how the AI parameters ρ and f influence the battery wholesale price $w^{BS\text{-}EA*}$, the EV retail price $p_v^{BS\text{-}EA*}$, the battery recycling price $p_r^{BS\text{-}EA*}$, and members' profits $\Pi_i^{BS\text{-}EA*}$ (for $i \in \{s, m\}$), as presented in Lemma 3.

Lemma 3. *In model BS-EA,*

(a) Both $w^{BS\text{-}EA*}$ and $p_v^{BS\text{-}EA*}$ are invariant with respect to ρ and f.
(b) The recycling price $p_r^{BS\text{-}EA*}$ and the profits $\Pi_i^{BS\text{-}EA*}$ are increasing in ρ and decreasing in f.

Lemma 3(a) shows that AI adoption does not influence wholesale or retail prices in the new-vehicle market. The equilibrium pricing structure, therefore, remains unchanged. Lemma 3(b) shows that higher AI reliability ρ increases the expected value recovered from RPBs. The EV manufacturer responds by offering a higher recycling price, which increases the RPB volume. The battery supplier benefits through its share of the increased volume of recovered batteries. In contrast, a higher AI service fee f reduces the net value generated from recycling. The EV manufacturer lowers the recycling price to preserve profitability. This reduction decreases the total value available for sharing and lowers the battery supplier's profit.

Since consumers' EV purchase decisions are solely determined by the retail price and are independent of recycling conditions, the forward and reverse channels are structurally decoupled from the demand side. The price-neutrality result is consistent across all three BS scenarios (NN, EN, EA) and is attributable to the model's separable demand structure. Because the retail and recycling prices enter the manufacturer's profit function additively and independently, as demonstrated in Eqs. (2), (4), and (6), the supplier's optimal wholesale price and the manufacturer's optimal retail price are determined solely by the forward-market parameters (a, b, c_n). In contrast, recycling-related parameters affect only the recycling price and, through it, reverse-channel profits.

5. Model analysis in battery leasing (BL)

In this section, we analyze the BL model using a Stackelberg game, where the battery supplier (leader) determines the wholesale price w, and the EV manufacturer (follower) selects the bundled access price p_t.

5.1. *No echelon utilization (model $BL - NN$)*

In this benchmark scenario, the EV manufacturer does not engage in echelon utilization. The profit functions are given in Eqs. (7) and (8).

$$\max_{\{w\}} \Pi_s^{BL\text{-}NN} = [w - c_n + (1-\phi)g]q_v \tag{7}$$

$$\max_{\{p_t\}} \Pi_m^{BL\text{-}NN} = [p_t - w + \phi g]q_v \tag{8}$$

We solve the game by backward induction. The equilibrium outcomes are summarized in Table 3.

Table 3. BL – Equilibrium results for scenarios $j \in \{NN, EN, EA\}$.

	NN	EN	EA
w^{j*}	$\frac{a+b\left[c_n+g(2\phi-1)\right]}{2b}$	$\frac{a+b\left[c_n+g(2\phi-1)+\alpha\beta k-(1-\alpha)(1-\beta)c_e-c_s\right]}{2b}$	$\frac{a+b\left[c_n+g(2\phi-1)+\alpha_A\beta k-(1-\beta)(1-\alpha_A)c_e-(1-\rho\sigma)c_s-f\right]}{2b}$
p_t^{j*}	$\frac{3a+b(c_n-g)}{4b}$	$\frac{3a+b\left[c_n-g-\alpha\beta k+(1-\alpha)(1-\beta)c_e+c_s\right]}{4b}$	$\frac{3a+b\left[c_n-g-\alpha_A\beta k+(1-\beta)(1-\alpha_A)c_e+(1-\rho\sigma)c_s+f\right]}{4b}$
q_v^{j*}	$\frac{a-b(c_n-g)}{4}$	$\frac{a-b\left[c_n-g-\alpha\beta k+(1-\alpha)(1-\beta)c_e+c_s\right]}{4}$	$\frac{a-b\left[c_n-g-\alpha_A\beta k+(1-\beta)(1-\alpha_A)c_e+(1-\rho\sigma)c_s+f\right]}{4}$
Π_s^{j*}	$\frac{\left[a-b(c_n-g)\right]^2}{8b}$	$\frac{\left[a-b(c_n-g-\alpha\beta k+(1-\alpha)(1-\beta)c_e+c_s)\right]^2}{8b}$	$\frac{\left[a-b(c_n-g-\alpha_A\beta k+(1-\beta)(1-\alpha_A)c_e+(1-\rho\sigma)c_s+f)\right]^2}{8b}$
Π_m^{j*}	$\frac{\left[a-b(c_n-g)\right]^2}{16b}$	$\frac{\left[a-b(c_n-g-\alpha\beta k+(1-\alpha)(1-\beta)c_e+c_s)\right]^2}{16b}$	$\frac{\left[a-b(c_n-g-\alpha_A\beta k+(1-\beta)(1-\alpha_A)c_e+(1-\rho\sigma)c_s+f)\right]^2}{16b}$

Based on Table 3, we examine how the parameters b and g influence the battery wholesale price $w^{BL\text{-}NN*}$, the bundled access price $p_t^{BL\text{-}NN*}$, and members' profits $\Pi_i^{BL\text{-}NN*}$ (for $i \in \{s, m\}$), as presented in Lemma 4.

Lemma 4. *In model BL-NN,*

(a) The wholesale price $w^{BL\text{-}NN*}$ is decreasing in b, and is decreasing in g when $\phi < \frac{1}{2}$, invariant with respect to g when $\phi = \frac{1}{2}$, and increasing in g when $\phi > \frac{1}{2}$.

(b) The bundled price $p_t^{BL\text{-}NN*}$ is decreasing in both b and g.

(c) The profits $\Pi_i^{BL\text{-}NN*}$ are decreasing in b, but increasing in g.

Lemma 4(a) demonstrates that increased market price sensitivity compels the supplier to lower the wholesale price. The impact of g depends on ϕ. When $\phi < \frac{1}{2}$, a higher g enhances the supplier's unit lifecycle gain, reducing reliance on wholesale margins and consequently lowering the wholesale price. When $\phi = \frac{1}{2}$, the residual value is shared equally, and the wholesale price remains invariant in g. When $\phi > \frac{1}{2}$, the supplier increases the wholesale price as g rises to recover the life cycle value through forward channels. Lemma 4(b) shows that the total access price decreases as b and g increase. When b is higher, margins shrink and the bundled access price drops. A higher g lowers the effective cost of battery service and shifts the recycling value into the total access price. Lemma 4(c) establishes that profits decrease as b increases because of margin compression, but increase with g since a higher per-unit margin and a lower bundled access price together increase demand. This compounded effect is unique to the BL model.

5.2. *Traditional echelon utilization (model BL − EN)*

We next consider the case where the EV manufacturer conducts echelon utilization without AI adoption. The profit functions are given in Eqs. (9) and (10).

$$\max_{\{w\}} \Pi_s^{BL\text{-}EN} = \big(w - c_n + (1-\phi)\,g\big)\,q_v \tag{9}$$

$$\max_{\{p_t\}} \Pi_m^{BL\text{-}EN} = \Big(p_t - w + \phi\,g + \alpha\beta k - (1-\alpha)(1-\beta)c_e - c_s\Big)\,q_v \tag{10}$$

Applying backward induction yields the equilibrium outcomes in Table 3.

Based on Table 3, we examine how the echelon utilization parameters k, α, c_e, and c_s influence the battery wholesale price $w^{BL\text{-}EN*}$, the bundled access price $p_t^{BL\text{-}EN*}$, and members' profits $\Pi_i^{BL\text{-}EN*}$ (for $i \in \{s, m\}$), as presented in Lemma 5.

Lemma 5. *In model BL-EN,*

(a) Both $w^{BL\text{-}EN*}$ and $\Pi_i^{BL\text{-}EN*}$ are increasing in α and k, but decreasing in c_e and c_s.
(b) The bundled price $p_t^{BL\text{-}EN*}$ is decreasing in α and k, but increasing in c_e and c_s.

Lemma 5(a) shows that as utilization becomes more favorable, leading to increases in α or k, the life-cycle value of each battery increases correspondingly. Consequently, the supplier raises the wholesale price to capture a portion of this additional value. Both firms benefit from the overall increase in total value. In contrast, higher values of c_e and c_s reduce the per-battery value and decrease profits for both parties. Lemma 5(b) demonstrates that the bundled access price responds in the opposite manner: when α or k increases, the manufacturer can profitably lower the access price, thereby stimulating demand and further enhancing profits. Conversely, when c_e or c_s rises, the manufacturer increases the access price to offset margin losses. This effect is more pronounced under BL than under BS, since the consumer access price is directly linked to reverse-channel value through integrated forward and reverse pricing.

5.3. *AI-enabled echelon utilization (model $BL - EA$)*

When the EV manufacturer uses AI to enhance sorting for echelon utilization, the profit functions for both parties are given by Eqs. (11) and (12).

$$\max_{\{w\}} \Pi_s^{BL\text{-}EA} = \big(w - c_n + (1-\phi)\, g\big)\, q_v \tag{11}$$

$$\max_{\{p_t\}} \Pi_m^{BL\text{-}EA} = \Big(p_t - w + \phi\, g + \alpha_A \beta k - (1-\beta)(1-\alpha_A)\, c_e - (1-\rho\sigma)\, c_s - f\Big)\, q_v \tag{12}$$

Applying backward induction yields the equilibrium outcomes in Table 3.

Based on Table 3, we examine how the AI parameters ρ and f influence the battery wholesale price $w^{BL\text{-}EA*}$, the bundled access price $p_t^{BL\text{-}EA*}$, and members' profits $\Pi_i^{BL\text{-}EA*}$ (for $i \in \{s, m\}$), as presented in Lemma 6.

Lemma 6. *In model BL-EA,*

(a) Both $w^{BL\text{-}EA*}$ and $\Pi_i^{BL\text{-}EA*}$ are increasing in ρ but decreasing in f.
(b) The bundled price $p_t^{BL\text{-}EA*}$ is decreasing in ρ but increasing in f.

Lemma 6(a) shows that higher AI reliability, ρ, raises the echelon utilization value. The supplier's response is to raise the wholesale price to obtain more reverse channel value. At the same time, both parties can still profit from the increase in total value throughout the life cycle. Conversely, an increase in the AI service fee reduces the net margin per RPB, which compels the supplier to lower the wholesale price and results in decreased profits for both parties. Lemma 6(b) shows that the bundled access price moves in the opposite direction. When ρ increases, higher efficiency enables the manufacturer to lower the bundled access price and pass some of the benefits to consumers. When f rises, the effective cost of leasing services increases, and the manufacturer raises the bundled access price so that consumers bear part of the cost.

Lemma 7. *In the BL model, for all scenarios $j \in \{NN, EN, EA\}$, the equilibrium profits of the battery supplier and the EV manufacturer satisfy*

$$\frac{\Pi_s^{BL\text{-}j*}}{\Pi_m^{BL\text{-}j*}} = 2.$$

Lemma 7 demonstrates that, under the BL model, the battery supplier's profit consistently remains twice that of the EV manufacturer. This constant ratio arises from Stackelberg leadership combined with linear demand and cost functions, which ensure that any change in reverse-channel value is proportionally reflected in both wholesale and bundled access prices. The fixed profit ratio eliminates potential conflicts of interest in technology investment decisions, as improvements in reverse-channel value benefit both parties proportionally. In contrast, under the BS model, the profit distribution varies with recycling responsiveness and reverse-channel value, which may result in misaligned incentives between the two parties.

6. Model analysis and comparison

We first analyze how echelon utilization and AI adoption by the EV manufacturer affect equilibrium decisions and outcomes under the two business models. All results are derived under the feasibility conditions summarized in Appendix A, which ensure positive demand, positive reverse-channel value, and interior equilibria. For expositional clarity, we define the following thresholds: For expositional clarity, we define the following thresholds: $f_1 = \rho\Big[(1-\alpha)(1-\beta)c_e + \sigma c_s\Big]$, $f_2 = \rho\Big[\sigma c_s + \frac{(1-\alpha)c_s}{\alpha} + \frac{(1-\alpha)(1-\beta)c_e}{\alpha}\Big]$, $k_1 = \frac{(1-\alpha)(1-\beta)c_e + c_s}{\alpha\beta}$, $k_2 = \frac{f+(1-\alpha)(1-\beta)(1-\rho)c_e+(1-\rho\sigma)c_s}{\alpha_A\beta}$, $k_3 = \frac{f-f_1}{(1-\alpha)\beta\rho}$. These thresholds are derived by comparing the EV manufacturer's equilibrium profits across (N,N), (E,N), and (E,A) and are proved in Appendix C.

Proposition 1. *Comparisons of the wholesale price w, retail price p_v, and bundled access price p_t across the three models (NN, EN, EA) are as follows:*

(a) In the BS model, both w and p_v are identical across all three models.
(b) In the BL model:
  - *(i) Echelon utilization effect: Comparing EN to NN, w increases and p_t decreases if and only if $k > k_1$; otherwise w decreases and p_t increases.*
  - *(ii) AI adoption effect: Comparing EA to EN, w increases and p_t decreases if either $f \le f_1$, or $f > f_1$ and $k > k_3$; otherwise w decreases and p_t increases.*
  - *(iii) Combined effect of echelon utilization with AI: Comparing EA to NN, w increases and p_t decreases if $k > k_2$; otherwise w decreases and p_t increases.*

Proposition 1 provides a comparative analysis of pricing under the BS and BL models. Part (a) demonstrates that, within the BS model, EV wholesale and retail prices remain consistent across (NN, EN, EA) because the recycling price is determined independently, and forward prices are influenced solely by EV demand and production costs. In contrast, part (b) shows that under BL, reverse-channel efficiency affects both the wholesale price and the bundled access price. When the unit echelon utilization value is sufficiently high, the battery supplier raises the wholesale price to capture more value. At the same time, electric vehicle manufacturers may pass some of this increased revenue to consumers by lowering usage costs, which stimulates demand.

Proposition 2. *The comparative results for equilibrium sales quantity q_v and recycling quantity q_r across the three models (NN, EN, EA) are as follows:*

(a) In the BS model:
  - *(i) The q_v remains unchanged across all three models.*
  - *(ii) Echelon utilization effect: Comparing EN to NN, q_r increases if $k > k_1$; otherwise, q_r decreases.*
  - *(iii) AI adoption effect: Comparing EA to EN, q_r increases if either $f \le f_1$, or $f > f_1$ and $k > k_3$; otherwise, q_r decreases.*

(iv) Combined effect of echelon utilization with AI: Comparing EA to NN, q_r increases if $k > k_2$; otherwise, q_r decreases.

(b) In the BL model:

(i) Echelon utilization effect: Comparing EN to NN, q_v increases if $k > k_1$; otherwise, q_v decreases.

(ii) AI adoption effect: Comparing EA to EN, q_v increases if either $f \leq f_1$, or $f > f_1$ and $k > k_3$; otherwise, q_v decreases.

(iii) Combined effect of echelon utilization with AI: Comparing EA to NN, q_v increases if $k > k_2$; otherwise, q_v decreases.

Proposition 2 describes how innovations affect equilibrium quantities under BS and BL. Under BS, innovations affect only the recycling stream. Consistent with part (a)(i) and Lemma 1(a), wholesale and retail prices remain constant, resulting in identical sales volumes across strategies. In contrast, the recycling quantity adheres to the threshold structure described in Proposition 1, as it is determined by the recycling price. Lemmas 2(b) and 3(b) demonstrate that an increase in the RPB value leads to a higher recycling price and greater returns, while a decrease has the opposite effect. Under BL, improvements in echelon utilization or AI adoption reduce the bundled access price and expand demand, so sales quantities follow the same threshold-driven pattern as prices.

By analyzing the EV manufacturer's equilibrium profits under both operating models, we derive optimal strategies for echelon utilization and AI adoption.

Proposition 3. *Comparing the EV manufacturer's equilibrium profits under (N, N), (E, N), and (E, A), the optimal strategy is:*

(a) The equilibrium strategy is (N, N) when either $0 < f \leq f_2$ and $0 < k \leq k_2$, or when $f > f_2$ and $0 < k \leq k_1$.

(b) The equilibrium strategy is (E, N) when $f > f_2$ and $k_1 < k \leq k_3$.

(c) The equilibrium strategy is (E, A) otherwise.

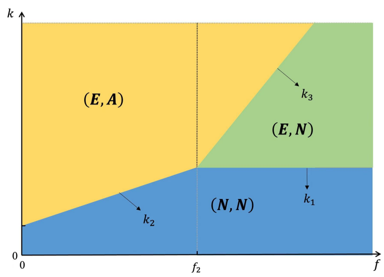


Fig. 3. Optimal strategy regions for the EV manufacturer.

Proposition 3 characterizes the optimal strategy for the EV manufacturer, as illustrated in Fig. 3. The boundaries between decision regions are determined by the trade-off between AI costs and the value generated through echelon utilization.

In region (N,N), the value of k is insufficient to cover sorting and disposal costs, resulting in the adoption of neither echelon utilization nor AI, even when f is small.

In region (E,N), echelon utilization is profitable, whereas AI adoption remains unprofitable. This region appears only when f is greater than f_2. When k is between k_1 and k_3, the cost of AI is higher than its efficiency benefits.

In the (E,A) region, both echelon utilization and AI are used. As f goes down, the (E,A) area grows a lot, while the (E,N) area gets smaller. This happens because lower AI costs make it less appealing to use echelon utilization without AI. So, when f decreases, members can move straight from the (N,N) area to the (E,A) area, skipping the (E,N) area.

The same strategic regions appear under both BS and BL models. Even though BS and BL have different pricing and demand responses, these differences do not change the profitability order of (N,N), (E,N), and (E,A). Thus, the EV manufacturer's technology adoption decision is primarily driven by reverse-channel value creation rather than by the specific forward-market transaction form.

We then examine how business model choice affects equilibrium pricing and demand.

Proposition 4. By comparing the equilibrium decisions under the BL and BS models, we obtain the following results:

(a) *The relative wholesale prices in the BL and BS models largely depend on the revenue-sharing parameter ϕ. For each scenario $j \in \{NN, EN, EA\}$, define the threshold ϕ_1^j as*

$$\phi_1^{NN} = \frac{1}{2}, \quad \phi_1^{EN} = \frac{1}{2} - \frac{k\alpha\beta - (1-\alpha)(1-\beta)c_e - c_s}{2g},$$
$$\phi_1^{EA} = \frac{1}{2} - \frac{\beta\alpha_A k - (1-\alpha_A)(1-\beta)c_e - (1-\rho\sigma)c_s - f}{2g}.$$

   (i) *If $\phi_1^j \in (0,1)$, then*
   $$w^{BL\text{-}j*} < w^{BS\text{-}j*} \quad \text{for } 0 < \phi < \phi_1^j, \qquad w^{BL\text{-}j*} > w^{BS\text{-}j*} \quad \text{for } \phi_1^j < \phi < 1.$$
   (ii) *If $\phi_1^j \le 0$, then $w^{BL\text{-}j*} > w^{BS\text{-}j*}$ for all $\phi \in (0,1)$.*
   (iii) *If $\phi_1^j \ge 1$, then $w^{BL\text{-}j*} < w^{BS\text{-}j*}$ for all $\phi \in (0,1)$.*

(b) *Under the feasibility conditions, the BL model yields a lower consumer's payment than the BS model, leading to a higher equilibrium demand.*

Proposition 4(a) explains how the revenue sharing parameter ϕ changes the difference in wholesale prices between BS and BL models. When ϕ is lower, battery suppliers keep most of the residual value. As a result, they lower the wholesale price to boost demand and generate a higher return on the life-cycle value. As ϕ increases, the supplier's share of the residual value shrinks, and its incentive to cut the wholesale price weakens. The threshold ϕ_1^j reflects how changes in the echelon utilization rate and AI adoption shift this trade-off relationship. A higher reverse channel value reduces ϕ_1^j and enlarges the range of ϕ for which the BL wholesale price is below the BS wholesale price.

Proposition 4(b) further shows that, relative to BS, the BL model reduces consumers' total payment. Under BL, consumers purchase a service rather than an asset that depreciates over time, so part of the reverse-channel value is translated into a lower access price. This makes EVs more attractive and further strengthens the BL model's demand advantage. This result relies on the assumption of homogeneous consumers who do not exhibit a preference for battery ownership, as discussed in Section 3.

Finally, we explore how the choice between BS and BL operating models influences the equilibrium profits of the EV manufacturers and the battery supplier.

Proposition 5. *Let V_j denote the EV manufacturer's unit net marginal value from the reverse channel under scenario $j \in \{NN, EN, EA\}$, as defined in Appendix A.1.*

(a) ***Manufacturer profitability.*** *For each scenario $j \in \{NN, EN, EA\}$, there exists a threshold $\bar{\theta}_m(V_j)$ such that*

$$\Pi_m^{BL\text{-}j*} < \Pi_m^{BS\text{-}j*} \quad \textit{if and only if} \quad \theta > \bar{\theta}_m(V_j),$$

where

$$\bar{\theta}_m(V_j) := \frac{2(a - bc_n)\big((1-\phi)g + V_j\big) + b\big((1-\phi)g + V_j\big)^2}{4V_j^2}.$$

(b) ***Supplier profitability.*** *For each scenario $j \in \{NN, EN, EA\}$, there exists a threshold $\bar{\theta}_s(V_j)$ such that*

$$\Pi_s^{BL\text{-}j*} < \Pi_s^{BS\text{-}j*} \quad \textit{if and only if} \quad \theta > \bar{\theta}_s(V_j),$$

where

$$\bar{\theta}_s(V_j) := \frac{2(a - bc_n)\big((1-\phi)g + V_j\big) + b\big((1-\phi)g + V_j\big)^2}{4(1-\phi)V_j g}.$$

Proposition 5 examines the profitability of the BS and BL models. The key factor is θ, which measures how much the recycling quantity changes in response to a change in the recycling price. When θ is low, price incentives do not have much effect on recycling. In this case, the BL model is more profitable because most of its value comes from EV sales rather than recycling. When θ is high, people react more to price incentives, so reverse channels become more economically important.

As technology improves and the value of V_j goes up, reverse channels become even more important. Proposition 5 shows that these changes make the BS model the best option in more cases, but the effect is different in each part of the supply chain. For the manufacturer, a higher V_j always lowers the point at which they prefer the BS model, so its best-use area grows. For the battery supplier, the effect of V_j is not straightforward because the parts of $\bar{\theta}_s(V_j)$ change in different ways as V_j changes, depending on the relative magnitudes of $(1-\phi)g$ and V_j.

7. Numerical analysis

In this section, we use numerical analysis to complement the analytical results by examining how key parameters shape equilibrium profits under the BS and

BL models. Following related closed-loop supply chain studies, we set the baseline parameters as follows.

Table 4. Baseline parameter values.

Source	Parameter	Value
Zhu *et al.* (2024)	a, c_n, g, k, c_s, β	10, 1, 0.4, 2, 0.5, 0.8
Wu *et al.* (2025)	b, c_e	1, 1
Niu *et al.* (2025)	ρ, f	0.9, 0.4

The remaining parameters are set at baseline values $\phi = 0.5$, $\sigma = 0.8$, $\alpha = 0.7$, $\theta = 1$. These calibration values are designed to reflect the actual operating conditions of the electric vehicle battery recycling market. In the sensitivity analysis, these four parameters vary within their respective ranges, while all other parameters retain their baseline values. In this way, the separate impact of each parameter on the equilibrium profit under the BS model and BL model can be examined.

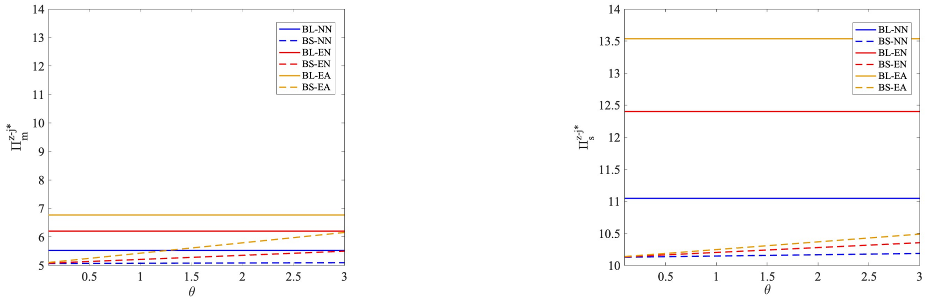
7.1. *Effect of recycling-price sensitivity θ*

The parameter $\theta \in [0.1, 3]$ is varied to examine how recycling-price sensitivity influences equilibrium profits under the BS and BL models across the three scenarios (NN, EN, EA), while all other parameters are held at their baseline values. The results are shown in Fig. 4.

In the BL model, profits are independent of θ for both parties because revenue is unaffected by recycling volume. In contrast, under the BS model, profits increase monotonically with θ as more responsive consumers return additional batteries, allowing firms to obtain greater reverse-channel revenue.

Moreover, the growth rate of BS profits varies across scenarios. The growth is slowest under NN, moderate under EN, and fastest under EA. This result aligns with expectations. AI enhances sorting quality and increases the value of recycled batteries. Consequently, as recycling volume increases, profit gains are greater under EA compared to EN or NN.

In addition, the EV manufacturer and battery supplier also respond to θ at different rates. The manufacturer's BS profits increase more rapidly, particularly under EA, whereas the supplier's profits grow more slowly. As recycling-price sensitivity rises, the two parties may develop divergent incentives, potentially influencing their collaboration within the supply chain.



(a) EV manufacturer's profits

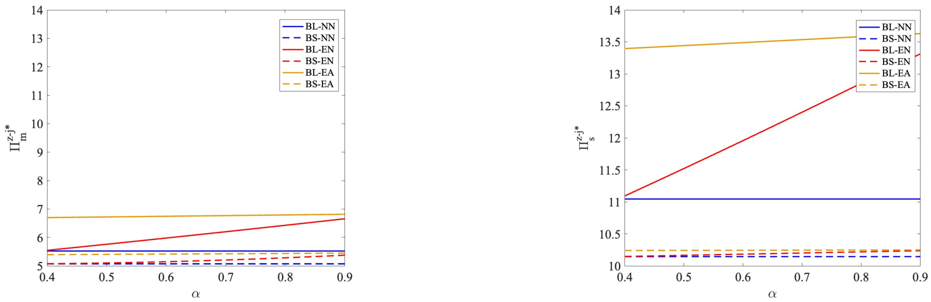
(b) Battery supplier's profits

Fig. 4. Effect of θ on equilibrium profits under the BL and BS models.

7.2. *Effect of baseline sorting accuracy* α

The parameter α is varied within $[0.4, 0.9]$ to evaluate the effect of baseline sorting accuracy on equilibrium profits for both models across three scenarios (NN, EN, EA), while all other parameters remain at their baseline values. Figure 5 presents the results.

In the NN scenario, profits for both parties remain unchanged as α varies because no sorting investment occurs. BS profits across all three scenarios are nearly insensitive to α. In contrast, under BL, increasing α substantially raises profit in the EN scenario but only modestly in the EA scenario. In EN, the manufacturer relies entirely on its own sorting capability, so higher baseline accuracy has a greater impact. In EA, AI directly compensates for lower baseline accuracy, resulting in profits that are largely independent of α.



(a) EV manufacturer's profits

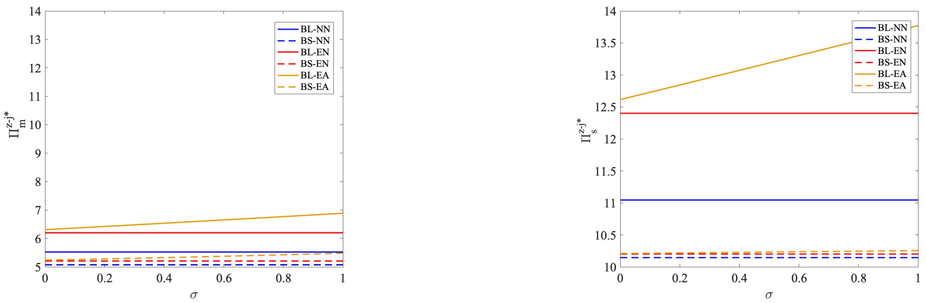
(b) Battery supplier's profits

Fig. 5. Effect of α on equilibrium profits under the BL and BS models.

7.3. *Effect of AI cost-reduction potential σ*

The parameter σ is varied over $[0, 1]$ to evaluate the impact of the cost reduction potential of AI on the equilibrium profit of BS and BL models under three scenarios (NN, EN, EA), while all other parameters are held at their baseline values. The corresponding results are shown in Fig. 6.

The parameter σ affects only the EA scenario. As σ increases, profits under both models rise as a result of reduced effective sorting costs and an enhanced value of the reverse channel. The BL model shows a larger profit increase, indicating that it transmits the value of the reverse channel more directly by bundling access prices. In the BS model, the profit of the EV manufacturer increases with σ to a greater extent than that of the battery supplier. This finding suggests that the manufacturer benefits more from AI cost reductions, since it bears a larger proportion of sorting-related costs and therefore gains more when these costs are reduced.



(a) EV manufacturer's profits

(b) Battery supplier's profits

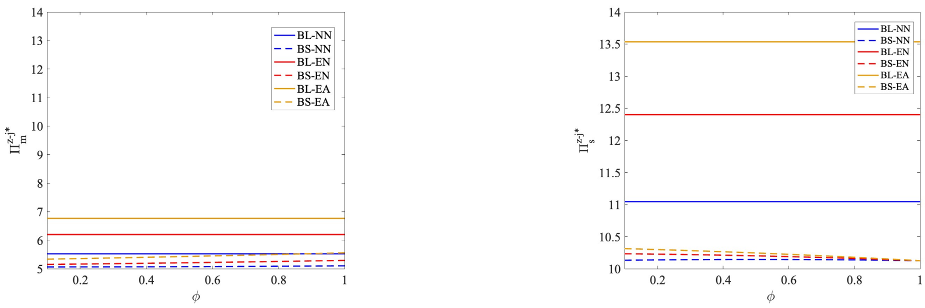
Fig. 6. Effect of σ on equilibrium profits under the BL and BS models.

7.4. *Effect of material recovery share ϕ*

The parameter ϕ is varied within the range $[0.05, 1]$ to assess the influence of material recovery share on equilibrium profits under the BS and BL models across the three scenarios (NN, EN, EA), with all other parameters maintained at their baseline values. The corresponding results are shown in Fig. 7.

BL profits remain constant across the full range of ϕ for both parties. Under BS, the EV manufacturer's profits increase gradually with ϕ, while the battery supplier's profits decline slightly, since the supplier's profit includes the term $(1 - \phi)$ and thus falls as the manufacturer retains a larger share of material recovery value.

Overall, variations in ϕ exert a limited influence on equilibrium profits for both parties. This finding indicates that the allocation of material recovery value between supply chain members does not substantially affect the relative profitability of the two business models in this context.



(a) EV manufacturer's profits

(b) Battery supplier's profits

Fig. 7. Impact of ϕ on profit between BL and BS models.

8. Conclusion

This paper develops a CLSC model for EV power batteries with a battery supplier and an EV manufacturer. The manufacturer decides whether to adopt echelon utilization and AI-based sorting under two business models, BS and BL. Using backward induction, we derive closed-form equilibria for prices, quantities, and profits across three operational settings under each of two business models, and then perform comparative statics and cross-model analysis to show how echelon utilization, AI, and business model choice jointly shape CLSC performance.

The results indicate that, under BS, reuse value does not influence the new EV price. In contrast, under BL, higher reuse value or AI-driven cost savings are reflected in the bundled access price, which directly influences EV demand. Furthermore, the analysis establishes threshold rules for the economic value of echelon utilization and AI investment, accounting for unit reuse value and AI services associated with both business models. The choice of the optimal business model depends on the sensitivity of recovery volume to price. When price sensitivity is low, the BL model is preferable, whereas the BS model is more appropriate when price sensitivity is high.

These findings offer several practical and policy implications:

(a) For EV manufacturers: Under BS, the recycling price should be regarded as the primary lever in the reverse channel. Higher recycling prices are warranted when consumer responsiveness or reuse value increases, as these prices improve collection rates without affecting the new-EV price. Under BL, manufacturers should incorporate echelon utilization value and AI-driven efficiency gains into the bundled access price. In the AI-adoption region, improvements in AI reliability should be leveraged to reduce the bundled access price, thereby increasing demand and capturing greater lifecycle value. Enhanced AI reliability also increases wholesale prices and profits for all supply chain participants.

(b) For battery suppliers: Battery suppliers gain from echelon utilization, particularly when AI enhances sorting accuracy and reduces costs. As channel leaders, they should promote the adoption of echelon utilization and AI by EV manufacturers, for instance, through improved buy-back terms or coordination contracts. Well-structured contracts can utilize reverse-flow income from RPBs to stabilize the system. The analysis also shows that in the BL model, the supplier's profit is always twice that of the manufacturer's, providing a solid basis for contract design based on reverse-flow income from RPBs.

(c) For policymakers: Although the current model does not explicitly incorporate government behavior, several findings suggest relevant policy recommendations. Subsidies that reduce the AI service fee can push echelon utilization above its adoption threshold, rendering it privately profitable. In markets where EV uptake is a priority, promoting the BL model and encouraging contract-based battery recycling, rather than depending solely on price incentives, can simultaneously increase EV demand and sustain supply chain profitability.

Several directions remain available for future work. First, adding carbon policy accounting to the battery life-cycle model would allow a more complete assessment of how AI contributes to sustainability goals, covering not only profits but also emissions and social costs. Second, analyzing competitive markets with asymmetric information could elucidate how AI-enabled data sharing and battery passports influence strategies and investments in battery reuse. Third, formally including government involvement, such as technology subsidies to support AI-based classification technologies and enhance the value of battery reuse, would enable systematic welfare analysis and provide more actionable policy recommendations.

Appendix A. Proofs for equilibrium

A.1. Preliminaries and feasibility conditions

Define the EV manufacturer's unit net marginal value from the reverse channel as V_j. For the three scenarios $j \in \{NN, EN, EA\}$, we have

$$V_{NN} = \phi g, \tag{A.1}$$

$$V_{EN} = \phi g + \alpha\beta k - (1-\alpha)(1-\beta)c_e - c_s, \tag{A.2}$$

$$V_{EA} = \phi g + \alpha_A \beta k - (1-\beta)(1-\alpha_A)c_e - (1-\rho\sigma)c_s - f, \quad \alpha_A = \alpha + \rho(1-\alpha). \tag{A.3}$$

Feasibility conditions We focus on interior solutions and impose the following assumptions.

(F1) **Positive primary-market demand.**

$$a - bc_n > 0. \tag{A.4}$$

This condition guarantees a strictly positive demand for new EVs; if $a - bc_n \le 0$, the primary market collapses and reverse-channel decisions become irrelevant.

(F2) **Bounded reverse-channel value.** For each scenario $j \in \{NN, EN, EA\}$,

$$0 < V_j < \bar{V}, \tag{A.5}$$

where

$$\bar{V} := \min\left\{\frac{a - bc_n}{2\theta},\ c_n - (1-\phi)g + \frac{3a}{b}\right\}. \tag{A.6}$$

The lower bound $V_j > 0$ ensures that RPBs are an asset rather than a disposal burden. The first upper bound $\frac{a-bc_n}{2\theta}$ guarantees that the recycling quantity does not exceed the sales quantity under BS, i.e., $q_r^{BS-j*} < q_v^{BS*}$. The second upper bound $c_n - (1-\phi)g + \frac{3a}{b}$ ensures that the bundled access price remains strictly positive under BL, i.e., $p_t^{BL-j*} > 0$, preventing a situation where the value of reverse channels is so high that consumers can essentially obtain EV for free.

A.2. Proof of Table 2 (BS-model equilibrium)

We derive the equilibrium outcomes for the three BS scenarios $j \in \{NN, EN, EA\}$ by backward induction. Using V_j, the profit functions are

$$\Pi_s^{BS-j} = (w - c_n)\, q_v^{BS} + (1-\phi)g\, q_r^{BS}, \tag{A.7}$$

$$\Pi_m^{BS-j} = (p_v - w)\, q_v^{BS} + (V_j - p_r)\, q_r^{BS}. \tag{A.8}$$

with demand and recycling functions

$$q_v^{BS} = a - bp_v, \qquad q_r^{BS} = \theta p_r. \tag{A.9}$$

Substituting (A.9) into (A.8), the manufacturer chooses (p_v, p_r) to maximize Π_m^{BS-j}. The Hessian

$$H_m^{BS-j} = \begin{bmatrix} -2b & 0 \\ 0 & -2\theta \end{bmatrix}$$

is negative definite, so the problem is jointly concave. The first-order conditions are

$$\frac{\partial \Pi_m^{BS-j}}{\partial p_v} = a - 2bp_v + bw = 0, \tag{A.10}$$

$$\frac{\partial \Pi_m^{BS-j}}{\partial p_r} = \theta(V_j - 2p_r) = 0. \tag{A.11}$$

Hence

$$p_v^{BS-j}(w) = \frac{a + bw}{2b}, \tag{A.12}$$

$$p_r^{BS-j*} = \frac{V_j}{2}. \tag{A.13}$$

and

$$q_v^{BS-j}(w) = a - b\, p_v^{BS-j}(w) = \frac{a - bw}{2}, \tag{A.14}$$

$$q_r^{BS-j*} = \theta\, p_r^{BS-j*} = \frac{\theta V_j}{2}. \tag{A.15}$$

Substituting (A.14) and (A.15) into (A.7) gives

$$\Pi_s^{BS-j}(w) = (w - c_n)\frac{a - bw}{2} + (1-\phi)g\,\frac{\theta V_j}{2}. \tag{A.16}$$

Since $\partial^2\Pi_s^{BS-j}/\partial w^2 = -b < 0$, the objective is strictly concave and the first-order condition yields

$$w^{BS-j*} = \frac{a + bc_n}{2b}. \tag{A.17}$$

Thus

$$p_v^{BS-j*} = \frac{3a + bc_n}{4b}. \tag{A.18}$$

Substituting w^{BS-j*}, p_v^{BS-j*}, and p_r^{BS-j*} into (A.9) and (A.7)–(A.8) yields the equilibrium quantities and profits reported in Table 2. This completes the proof.

A.3. Proof of Table 3 (BL-model equilibrium)

We next derive the equilibrium outcomes for the three BL scenarios $j \in \{NN, EN, EA\}$ by backward induction.
Using V_j, the profit functions are

$$\Pi_s^{BL-j} = \big(w - c_n + (1-\phi)g\big)\, q_v^{BL}, \tag{A.19}$$

$$\Pi_m^{BL-j} = \big(p_t - w + V_j\big)\, q_v^{BL}, \tag{A.20}$$

with demand

$$q_v^{BL} = a - bp_t. \tag{A.21}$$

Substituting (A.21) into (A.20), the manufacturer solves

$$\max_{p_t}\ (p_t - w + V_j)(a - bp_t), \tag{A.22}$$

whose objective is strictly concave since $\partial^2\Pi_m^{BL-j}/\partial p_t^2 = -2b < 0$. The first-order condition gives

$$p_t^{BL-j}(w) = \frac{a + b(w - V_j)}{2b}, \tag{A.23}$$

and hence

$$q_v^{BL-j}(w) = a - bp_t^{BL-j}(w) = \frac{a - b(w - V_j)}{2}. \tag{A.24}$$

Substituting (A.24) into (A.19) yields

$$\max_{w}\ \big(w - c_n + (1-\phi)g\big)\frac{a - b(w - V_j)}{2}, \tag{A.25}$$

which is strictly concave in w since $\partial^2\Pi_s^{BL-j}/\partial w^2 = -b < 0$. The first-order condition gives

$$w^{BL-j*} = \frac{a + b\big[c_n - (1-\phi)g + V_j\big]}{2b}. \tag{A.26}$$

Substituting (A.26) into (A.23) gives

$$p_t^{BL-j*} = \frac{3a + b\big[c_n - (1-\phi)g - V_j\big]}{4b}. \tag{A.27}$$

Substituting w^{BL-j*} and p_t^{BL-j*} into (A.21) and (A.19)–(A.20) yields the equilibrium quantities and profits reported in Table 3. This completes the proof.

B.1. Proofs of Lemmas 1–3 (BS model)

Lemma 1 (NN). In the NN case, $V_{NN} = \phi g$. Differentiating the expressions in Table 2 with respect to b gives

$$\frac{\partial w^{BS\text{-}NN*}}{\partial b} = -\frac{a}{2b^2} < 0, \qquad \frac{\partial p_v^{BS\text{-}NN*}}{\partial b} = -\frac{3a}{4b^2} < 0, \qquad \frac{\partial p_r^{BS\text{-}NN*}}{\partial b} = 0,$$

and, using $a > bc_n$,

$$\frac{\partial \Pi_i^{BS\text{-}NN*}}{\partial b} = -\frac{(a - bc_n)(a + bc_n)}{K_i\, b^2} < 0, \qquad K_s = 8,\ K_m = 16,\ i \in \{s, m\}.$$

Thus a higher b (more price-sensitive demand) reduces both prices and profits.
Since $w^{BS\text{-}NN*}$ and $p_v^{BS\text{-}NN*}$ do not depend on g while $p_r^{BS\text{-}NN*} = \phi g/2$, we obtain

$$\frac{\partial p_r^{BS\text{-}NN*}}{\partial g} = \frac{\phi}{2} > 0, \qquad \frac{\partial \Pi_m^{BS\text{-}NN*}}{\partial g} = \frac{\theta\phi^2 g}{2} > 0, \qquad \frac{\partial \Pi_s^{BS\text{-}NN*}}{\partial g} = \theta(1-\phi)\phi g > 0.$$

Hence a higher residual value g raises the recycling price and both parties' profits, proving Lemma 1.

Lemma 2 (EN). For BS–EN, Table 2 implies that $w^{BS\text{-}EN*}$ and $p_v^{BS\text{-}EN*}$ are independent of k, α, c_e, c_s, so

$$\frac{\partial w^{BS\text{-}EN*}}{\partial x} = \frac{\partial p_v^{BS\text{-}EN*}}{\partial x} = 0, \qquad x \in \{k, \alpha, c_e, c_s\},$$

which proves Lemma 2(a).
From Table 2,

$$\frac{\partial p_r^{BS\text{-}EN*}}{\partial k} = \frac{\alpha\beta}{2} > 0, \quad \frac{\partial p_r^{BS\text{-}EN*}}{\partial \alpha} = \frac{\beta k + (1-\beta)c_e}{2} > 0,$$
$$\frac{\partial p_r^{BS\text{-}EN*}}{\partial c_e} = -\frac{(1-\alpha)(1-\beta)}{2} < 0, \quad \frac{\partial p_r^{BS\text{-}EN*}}{\partial c_s} = -\frac{1}{2} < 0.$$

Moreover, the equilibrium profits can be written as affine functions of $p_r^{BS\text{-}EN*}$:

$$\Pi_m^{BS\text{-}EN*} = \frac{(a - bc_n)^2}{16b} + \frac{\theta}{2} V_{EN}\, p_r^{BS\text{-}EN*}, \Pi_s^{BS\text{-}EN*} = \frac{(a - bc_n)^2}{8b} + \theta(1-\phi) g\, p_r^{BS\text{-}EN*},$$

with $V_{EN} > 0$ (Appendix A.1). Since the coefficients of $p_r^{BS\text{-}EN*}$ are positive, $\Pi_i^{BS\text{-}EN*}$ inherit the same monotonicity as $p_r^{BS\text{-}EN*}$ in k, α, c_e, c_s, proving Lemma 2(b).

Lemma 3 (EA). For BS–EA, $w^{BS\text{-}EA*}$ and $p_v^{BS\text{-}EA*}$ again depend only on (a, b, c_n) and are independent of ρ and f. Hence

$$\frac{\partial w^{BS\text{-}EA*}}{\partial x} = \frac{\partial p_v^{BS\text{-}EA*}}{\partial x} = 0, \qquad x \in \{\rho, f\},$$

which is Lemma 3(a).
The recycling price is $p_r^{BS\text{-}EA*} = V_{EA}/2$, where (Appendix A.1)

$$\frac{\partial V_{EA}}{\partial \rho} = (1-\alpha)\beta k + (1-\beta)(1-\alpha)c_e + \sigma c_s > 0, \qquad \frac{\partial V_{EA}}{\partial f} = -1 < 0,$$

so

$$\frac{\partial p_r^{BS\text{-}EA*}}{\partial \rho} > 0, \qquad \frac{\partial p_r^{BS\text{-}EA*}}{\partial f} < 0.$$

From Table 2, the equilibrium profits can be expressed as

$$\Pi_m^{BS\text{-}EA*} = \frac{(a-bc_n)^2}{16b} + \frac{b\theta}{4}V_{EA}^2, \qquad \Pi_s^{BS\text{-}EA*} = \frac{(a-bc_n)^2}{8b} + \frac{\theta(1-\phi)g}{2}V_{EA},$$

so

$$\frac{\partial \Pi_m^{BS\text{-}EA*}}{\partial V_{EA}} = \frac{\theta}{2}V_{EA} > 0, \qquad \frac{\partial \Pi_s^{BS\text{-}EA*}}{\partial V_{EA}} = \frac{\theta(1-\phi)g}{2} > 0.$$

Combining with the signs of $\partial V_{EA}/\partial \rho$ and $\partial V_{EA}/\partial f$ yields

$$\frac{\partial \Pi_i^{BS\text{-}EA*}}{\partial \rho} > 0, \qquad \frac{\partial \Pi_i^{BS\text{-}EA*}}{\partial f} < 0, \quad i \in \{s, m\},$$

that is, higher AI reliability raises the recycling price and both parties' profits, whereas a higher per–unit AI service fee reduces them, which proves Lemma 3(b).

B.2. Proofs of Lemmas 4–6 (BL model)

Lemma 4 (NN). In model BL–NN, the equilibrium outcomes are given in Table 3. Direct differentiation of $w^{BL\text{-}NN*}$ and $p_t^{BL\text{-}NN*}$ with respect to b and g gives

$$\frac{\partial w^{BL\text{-}NN*}}{\partial b} = -\frac{a}{2b^2} < 0, \qquad \frac{\partial w^{BL\text{-}NN*}}{\partial g} = \frac{2\phi - 1}{2},$$

$$\frac{\partial p_t^{BL\text{-}NN*}}{\partial b} = -\frac{3a}{4b^2} < 0, \qquad \frac{\partial p_t^{BL\text{-}NN*}}{\partial g} = -\frac{1}{4} < 0.$$

Hence $w^{BL\text{-}NN*}$ is decreasing in b, decreasing in g when $\phi < \frac{1}{2}$, invariant with respect to g when $\phi = \frac{1}{2}$, and increasing in g when $\phi > \frac{1}{2}$. The bundled access price $p_t^{BL\text{-}NN*}$ is decreasing in both b and g. The sales quantity is

$$q_v^{BL\text{-}NN*} = \frac{1}{4}\Big[a - b\big(c_n - g\big)\Big],$$

where

$$\frac{\partial q_v^{BL\text{-}NN*}}{\partial b} = -\frac{c_n - g}{4} < 0 \quad \text{since } 0 < g < c_n, \frac{\partial q_v^{BL\text{-}NN*}}{\partial g} = \frac{b}{4} > 0.$$

Thus $q_v^{BL\text{-}NN*}$ is decreasing in b and increasing in g.
From Table 3,

$$\Pi_s^{BL\text{-}NN*} = \frac{2}{b}\big(q_v^{BL\text{-}NN*}\big)^2, \qquad \Pi_m^{BL\text{-}NN*} = \frac{1}{b}\big(q_v^{BL\text{-}NN*}\big)^2,$$

so $\Pi_s^{BL\text{-}NN*}$ and $\Pi_m^{BL\text{-}NN*}$ share the same monotonicity as $q_v^{BL\text{-}NN*}$. Therefore both profits are decreasing in b and increasing in g, proving Lemma 4(c). This completes the proof of Lemma 4.

Lemma 5 (EN). In model BL–EN, the equilibrium outcomes are given in Table 3 and V_{EN} is defined in Appendix A.1. Direct differentiation of $w^{BL\text{-}EN*}$ and $p_t^{BL\text{-}EN*}$ with respect to k, α, c_e, c_s gives

$$\frac{\partial w^{BL\text{-}EN*}}{\partial k} = \frac{\alpha\beta}{2} > 0, \qquad \frac{\partial w^{BL\text{-}EN*}}{\partial \alpha} = \frac{\beta k + (1-\beta)c_e}{2} > 0,$$

$$\frac{\partial w^{BL\text{-}EN*}}{\partial c_e} = -\frac{(1-\alpha)(1-\beta)}{2} < 0, \qquad \frac{\partial w^{BL\text{-}EN*}}{\partial c_s} = -\frac{1}{2} < 0,$$

and

$$\frac{\partial p_t^{BL\text{-}EN*}}{\partial k} = -\frac{\alpha\beta}{4} < 0, \qquad \frac{\partial p_t^{BL\text{-}EN*}}{\partial \alpha} = -\frac{\beta k + (1-\beta)c_e}{4} < 0,$$

$$\frac{\partial p_t^{BL\text{-}EN*}}{\partial c_e} = \frac{(1-\alpha)(1-\beta)}{4} > 0, \qquad \frac{\partial p_t^{BL\text{-}EN*}}{\partial c_s} = \frac{1}{4} > 0.$$

Hence $w^{BL\text{-}EN*}$ increases in k and α and decreases in c_e and c_s, while $p_t^{BL\text{-}EN*}$ moves in the opposite direction.

The sales quantity is

$$q_v^{BL\text{-}EN*} = \frac{1}{4}\Big[a - b\big(c_n - (1-\phi)g - V_{EN}\big)\Big],$$

where

$$\frac{\partial V_{EN}}{\partial k} = \alpha\beta > 0, \qquad \frac{\partial V_{EN}}{\partial \alpha} = \beta k + (1-\beta)c_e > 0,$$

$$\frac{\partial V_{EN}}{\partial c_e} = -(1-\alpha)(1-\beta) < 0, \qquad \frac{\partial V_{EN}}{\partial c_s} = -1 < 0.$$

Thus $q_v^{BL\text{-}EN*}$ is increasing in k and α and decreasing in c_e and c_s.

From Table 3,

$$\Pi_s^{BL\text{-}EN*} = \frac{2}{b}\big(q_v^{BL\text{-}EN*}\big)^2, \qquad \Pi_m^{BL\text{-}EN*} = \frac{1}{b}\big(q_v^{BL\text{-}EN*}\big)^2,$$

so $\Pi_s^{BL\text{-}EN*}$ and $\Pi_m^{BL\text{-}EN*}$ share the same monotonicity as $q_v^{BL\text{-}EN*}$. Therefore $w^{BL\text{-}EN*}$ and $\Pi_i^{BL\text{-}EN*}$ $(i \in \{s, m\})$ increase in k and α and decrease in c_e and c_s, while $p_t^{BL\text{-}EN*}$ moves in the opposite direction, proving Lemma 5.

Lemma 6 (EA). Using Table 3, differentiation yields

$$\frac{\partial w^{BL\text{-}EA*}}{\partial \rho} = \frac{B}{2} > 0, \qquad \frac{\partial w^{BL\text{-}EA*}}{\partial f} = -\frac{1}{2} < 0,$$

and

$$\frac{\partial p_t^{BL\text{-}EA*}}{\partial \rho} = -\frac{B}{4} < 0, \qquad \frac{\partial p_t^{BL\text{-}EA*}}{\partial f} = \frac{1}{4} > 0,$$

where

$$B := (1-\alpha)\beta k + (1-\beta)(1-\alpha)c_e + \sigma c_s > 0.$$

The sales quantity is

$$q_v^{BL\text{-}EA*} = \frac{1}{4}\Big[a - b\big(c_n - (1-\phi)g - \alpha_A\beta k + (1-\beta)(1-\alpha_A)c_e + (1-\rho\sigma)c_s + f\big)\Big],$$

with $\alpha_A = \alpha + \rho(1-\alpha)$, so

$$\frac{\partial q_v^{BL\text{-}EA*}}{\partial \rho} = \frac{bB}{4} > 0, \qquad \frac{\partial q_v^{BL\text{-}EA*}}{\partial f} = -\frac{b}{4} < 0.$$

From Table 3,

$$\Pi_s^{BL\text{-}EA*} = \frac{2}{b}\big(q_v^{BL\text{-}EA*}\big)^2, \qquad \Pi_m^{BL\text{-}EA*} = \frac{1}{b}\big(q_v^{BL\text{-}EA*}\big)^2,$$

so for $q_v^{BL\text{-}EA*} > 0$, both profits increase in $q_v^{BL\text{-}EA*}$ and therefore increase in ρ and decrease in f. This completes the proof of Lemma 6.

B.3. Proof of Lemma 7

For all $j \in \{NN, EN, EA\}$,

$$\frac{\Pi_s^{BL\text{-}j*}}{\Pi_m^{BL\text{-}j*}} = \frac{\frac{\left[a-b(c_n-(1-\phi)g-V_j^{BL})\right]^2}{8b}}{\frac{\left[a-b(c_n-(1-\phi)g-V_j^{BL})\right]^2}{16b}} = 2.$$

Hence, the battery supplier's equilibrium profit is exactly twice that of the EV manufacturer in the BL model, completing the proof of Lemma 7.

Appendix C. Proofs for Propositions

C.1. Proof of Proposition 1

We compare the equilibrium pricing decisions across the three models (NN, EN, EA) under the two business models.

(a) **BS model**

From Table 2, the equilibrium wholesale and retail prices in the BS model depend only on (a, b, c_n) and are therefore identical across (NN, EN, EA). Hence w and p_v remain unchanged across the three models, which proves part (a).

(b) **BL model**

(i) *Echelon utilization effect (EN vs. NN).* Comparing EN and NN in Table 3 gives

$$w^{BL\text{-}EN*} - w^{BL\text{-}NN*} = \frac{\alpha\beta k - (1-\alpha)(1-\beta)c_e - c_s}{2}. \tag{C.1}$$

Define

$$k_1 = \frac{(1-\alpha)(1-\beta)c_e + c_s}{\alpha\beta}.$$

Then $\alpha\beta k - (1-\alpha)(1-\beta)c_e - c_s > 0$ if $k > k_1$. Accordingly, when $k > k_1$, echelon utilization raises the wholesale price; otherwise w falls.

(ii) *AI adoption effect (EA vs. EN).* Comparing EA and EN in Table 3 yields

$$w^{BL\text{-}EA*} - w^{BL\text{-}EN*} = \frac{\rho\Big[(1-\alpha)\beta k + (1-\alpha)(1-\beta)c_e + \sigma c_s\Big] - f}{2}. \tag{C.2}$$

Define

$$f_1 = \rho\big[(1-\alpha)(1-\beta)c_e + \sigma c_s\big], \qquad k_3 = \frac{f - f_1}{(1-\alpha)\beta\rho}.$$

Then $w^{BL\text{-}EA*} > w^{BL\text{-}EN*}$ if either $f \leq f_1$, or $f > f_1$ and $k > k_3$; otherwise $w^{BL\text{-}EA*} < w^{BL\text{-}EN*}$.

(iii) *Combined effect of echelon utilization and AI (EA vs. NN).* Comparing EA and NN gives

$$w^{BL\text{-}EA*} - w^{BL\text{-}NN*} = \frac{\alpha_A\beta k - (1-\alpha)(1-\beta)(1-\rho)c_e - (1-\rho\sigma)c_s - f}{2}. \tag{C.3}$$

Define

$$k_2 = \frac{f + (1-\alpha)(1-\beta)(1-\rho)c_e + (1-\rho\sigma)c_s}{\alpha_A \beta}.$$

Then $w^{BL\text{-}EA*} > w^{BL\text{-}NN*}$ if $k > k_2$, and $w^{BL\text{-}EA*} < w^{BL\text{-}NN*}$ otherwise.

From Table 3, in each comparison above the difference in bundled access prices is exactly one half of the difference in wholesale prices with the opposite sign. Thus p_t always moves in the opposite direction to w, and the statements about p_t in Proposition 1(b) follow directly from the analysis for w. Combining parts (a) and (b) completes the proof of Proposition 1.

C.2. Proof of Proposition 2

We compare the equilibrium quantities across the three models $j \in \{NN, EN, EA\}$.

(a) **BS model**

From Table 2, the equilibrium sales quantity is

$$q_v^{BS*} = \frac{a - bc_n}{4}, \tag{C.4}$$

which does not depend on j. Hence q_v is identical across NN, EN, and EA, proving part (a)(i).

The equilibrium recycling quantity is

$$q_r^{BS-j*} = \frac{\theta V_j}{2}, \tag{C.5}$$

so q_r^{BS-j*} is strictly increasing in the reverse–channel value V_j.

In Proposition 1, the expressions for V_j were used to derive the thresholds k_1, k_2, k_3 and f_1 that determine the sign of $V_{j_1} - V_{j_2}$ for the pairs (EN,NN), (EA,EN), and (EA,NN). Since q_r^{BS-j*} is an affine function of V_j with positive coefficient $\theta/2$, the sign of $q_r^{BS\text{-}j_1*} - q_r^{BS\text{-}j_2*}$ coincides with the sign of $V_{j_1} - V_{j_2}$, and thus follows exactly the same threshold conditions as in Proposition 1. This yields parts (a)(ii)–(iv).

(b) **BL model**

From Table 3, the equilibrium sales quantity is

$$q_v^{BL-j*} = \frac{a - b\big[c_n - (1-\phi)g - V_j\big]}{4}, \tag{C.6}$$

so

$$\frac{\partial q_v^{BL-j*}}{\partial V_j} = \frac{b}{4} > 0.$$

Hence q_v^{BL-j*} is strictly increasing in V_j.

Combining parts (a) and (b) completes the proof of Proposition 2.

C.3. Proof of Proposition 3

We compare the EV manufacturer's equilibrium profits under the three strategy profiles (N, N), (E, N), and (E, A) in both the BS and BL models.

(a) **BS model**

(i) *Comparing* (E, N) *and* (N, N). The profit difference between EN and NN is

$$\Pi_m^{BS\text{-}EN*} - \Pi_m^{BS\text{-}NN*} = \frac{\theta}{4}\big(V_{EN} - \phi g\big)\big(V_{EN} + \phi g\big). \tag{C.7}$$

Since $\theta > 0$ and $V_{EN} + \phi g > 0$ under the feasibility conditions, the sign of (C.7) is determined by $V_{EN} - \phi g$. Thus $\Pi_m^{BS\text{-}EN*} > \Pi_m^{BS\text{-}NN*}$ if $k > k_1$.

(ii) *Comparing* (E, A) *and* (N, N). The profit difference between EA and NN is

$$\Pi_m^{BS\text{-}EA*} - \Pi_m^{BS\text{-}NN*} = \frac{\theta}{4}\big(V_{EA} - \phi g\big)\big(V_{EA} + \phi g\big). \tag{C.8}$$

Under the feasibility conditions, $V_{EA} + \phi g > 0$ holds. Hence $\Pi_m^{BS\text{-}EA*} > \Pi_m^{BS\text{-}NN*}$ if $k > k_2$.

(iii) *Comparing* (E, A) *and* (E, N). The profit difference between EA and EN is

$$\Pi_m^{BS\text{-}EA*} - \Pi_m^{BS\text{-}EN*} = \frac{\theta}{4}\Big[\rho(1-\alpha)\beta k + f_1 - f\Big]\big(V_{EA} + V_{EN}\big). \tag{C.9}$$

Since $V_{EA} + V_{EN} > 0$ under feasibility, $\Pi_m^{BS\text{-}EA*} > \Pi_m^{BS\text{-}EN*}$ holds if either $0 < f \le f_1$, or $f > f_1$ and $k > k_3$.

We next compare the EV manufacturer's equilibrium profits under (N, N), (E, N), and (E, A) in the BL model.

(b) **BL model**

(i) *Comparing* (E, N) *and* (N, N). The profit difference between EN and NN is

$$\Pi_m^{BL\text{-}EN*} - \Pi_m^{BL\text{-}NN*} = \frac{1}{16}\big(V_{EN} - \phi g\big)\big[b\big(V_{EN} - \phi g + 2g\big) + 2(a - bc_n)\big]. \tag{C.10}$$

Under the feasibility conditions of the BL model,

$$b\big(V_{EN} - \phi g + 2g\big) + 2(a - bc_n) > 0$$

holds, so the sign of (C.10) is again determined by $V_{EN} - \phi g$. Therefore $\Pi_m^{BL\text{-}EN*} > \Pi_m^{BL\text{-}NN*}$ if $k > k_1$.

(ii) *Comparing* (E, A) *and* (N, N). The profit difference between EA and NN is

$$\Pi_m^{BL\text{-}EA*} - \Pi_m^{BL\text{-}NN*} = \frac{1}{16}\big(V_{EA} - \phi g\big)\big[b\big(V_{EA} - \phi g + 2g\big) + 2(a - bc_n)\big]. \tag{C.11}$$

Feasibility implies

$$b\big(V_{EA} - \phi g + 2g\big) + 2(a - bc_n) > 0,$$

so $\Pi_m^{BL\text{-}EA*} > \Pi_m^{BL\text{-}NN*}$ if $k > k_2$.

(iii) *Comparing* (E, A) *and* (E, N). The profit difference between EA and EN is

$$\Pi_m^{BL\text{-}EA*} - \Pi_m^{BL\text{-}EN*} = \frac{1}{16}\Big[\rho(1-\alpha)\beta k + f_1 - f\Big]\big[b\big(V_{EN} + V_{EA} + 2(1-\phi)g\big) + 2(a - bc_n)\big]. \tag{C.12}$$

Under feasibility, $b\big(V_{EN} + V_{EA} + 2(1-\phi)g\big) + 2(a - bc_n) > 0$ holds. Hence $\Pi_m^{BL\text{-}EA*} > \Pi_m^{BL\text{-}EN*}$ if either $0 < f \le f_1$, or $f > f_1$ and $k > k_3$.

We find that the resulting profit rankings and strategy regions are identical under the BS and BL models. Therefore, we suppress the model index and write Π_m^{j*} for the EV manufacturer's equilibrium profit under strategy $j \in \{NN, EN, EA\}$ in the ranking analysis below.

We first establish the ordering of k_1, k_2, and k_3 as a function of f.

Comparison of k_1 and k_2.

$$k_1 - k_2 = \frac{(1-\alpha)(1-\beta)c_e + c_s}{\alpha\beta} - \frac{f + (1-\alpha)(1-\beta)(1-\rho)c_e + (1-\rho\sigma)c_s}{\alpha_A\beta}.$$

Substituting $\alpha_A = \alpha + \rho(1-\alpha)$ and simplifying yields

$$k_1 - k_2 = \frac{\rho\big[(1-\alpha)(1-\beta)c_e + (1-\alpha+\alpha\sigma)c_s\big] - \alpha f}{\alpha\alpha_A\beta}.$$

Since $\alpha\alpha_A\beta > 0$, we have $k_1 > k_2$ if and only if $f < f_2$. Turning to k_3, observe that $k_3 = \frac{f-f_1}{(1-\alpha)\beta\rho}$ and $(1-\alpha)\beta\rho > 0$, so

$$k_3 \leq 0 \quad \text{if } f \leq f_1 \qquad \text{and} \qquad k_3 > 0 \quad \text{if } f > f_1.$$

(a) When $f \leq f_1$, $k_3 \leq 0 < k_1$ and $k_3 \leq 0 < k_2$, so $k_3 < k_1$ and $k_3 < k_2$ are satisfied.

(b) When $f > f_1$, $k_3 > 0$ and further analysis is needed to compare k_3 with k_1 and k_2.

(i) Comparison of k_1 and k_3 (when $f > f_1$).

$$k_1 - k_3 = \frac{(1-\alpha)(1-\beta)c_e + c_s}{\alpha\beta} - \frac{f - f_1}{(1-\alpha)\beta\rho}.$$

Simplifying yields

$$k_1 - k_3 = \frac{\rho\big[(1-\alpha)(1-\beta)c_e + (1-\alpha+\alpha\sigma)c_s\big] - \alpha f}{\alpha(1-\alpha)\beta\rho}.$$

Since $\alpha(1-\alpha)\beta\rho > 0$, we have $k_1 > k_3$ if and only if $f < f_2$.

(ii) Comparison of k_2 and k_3 (when $f > f_1$).

$$k_2 - k_3 = \frac{f + (1-\alpha)(1-\beta)(1-\rho)c_e + (1-\rho\sigma)c_s}{\alpha_A\beta} - \frac{f - f_1}{(1-\alpha)\beta\rho}.$$

Simplifying yields

$$k_2 - k_3 = \frac{\rho\big[(1-\alpha)(1-\beta)c_e + (1-\alpha+\alpha\sigma)c_s\big] - \alpha f}{\alpha_A(1-\alpha)\beta\rho}.$$

Since $\alpha_A(1-\alpha)\beta\rho > 0$, we have $k_2 > k_3$ if and only if $f < f_2$. The above analysis establishes the following threshold ordering:

(a) $k_3 \leq 0 < k_2 < k_1$ when $f \leq f_1$,

(b) $0 < k_3 < k_2 < k_1$ when $f_1 < f \leq f_2$,

(c) $0 < k_1 < k_2 < k_3$ when $f > f_2$.

These orderings underlie the case structure in the profit ranking below.

Profit ranking and equilibrium strategy.

(a) If $0 < f \leq f_1$ (so $k_1 > k_2 > k_3$), then $0 < k < k_2$: $\Pi_m^{NN*} > \Pi_m^{EA*} > \Pi_m^{EN*}$; $k_2 < k < k_1$: $\Pi_m^{EA*} > \Pi_m^{NN*} > \Pi_m^{EN*}$; $k > k_1$: $\Pi_m^{EA*} > \Pi_m^{EN*} > \Pi_m^{NN*}$.

(b) If $f_1 < f \leq f_2$ (so $k_1 > k_2 > k_3$), then $0 < k < k_3$: $\Pi_m^{NN*} > \Pi_m^{EN*} > \Pi_m^{EA*}$; $k_3 < k < k_2$: $\Pi_m^{NN*} > \Pi_m^{EA*} > \Pi_m^{EN*}$; $k_2 < k < k_1$: $\Pi_m^{EA*} > \Pi_m^{NN*} > \Pi_m^{EN*}$; $k > k_1$: $\Pi_m^{EA*} > \Pi_m^{EN*} > \Pi_m^{NN*}$.

(c) If $f > f_2$ (so $k_3 > k_2 > k_1$), then $0 < k < k_1$: $\Pi_m^{NN*} > \Pi_m^{EN*} > \Pi_m^{EA*}$; $k_1 < k < k_2$: $\Pi_m^{EN*} > \Pi_m^{NN*} > \Pi_m^{EA*}$; $k_2 < k < k_3$: $\Pi_m^{EN*} > \Pi_m^{EA*} > \Pi_m^{NN*}$; $k > k_3$: $\Pi_m^{EA*} > \Pi_m^{EN*} > \Pi_m^{NN*}$.
Combining the above cases yields the equilibrium strategy regions stated in Proposition 3.

C.4. Proof of Proposition 4

We compare the equilibrium outcomes under the BS and BL models for the three scenarios $j \in \{NN, EN, EA\}$, using the unified reverse-channel value V_j defined in Appendix A.1.

(a) **Comparison of wholesale prices**

Using Appendix A.1 and Tables 2–3, the wholesale price difference between the BL and BS models can be written, for any $j \in \{NN, EN, EA\}$, as

$$w^{BL\text{-}j*} - w^{BS\text{-}j*} = \frac{1}{2}\big[V_j - (1-\phi)g\big],$$

where V_j is the reverse-channel value under scenario j. Hence $w^{BL\text{-}j*}$ is linear in ϕ and

$$w^{BL\text{-}j*} < w^{BS\text{-}j*} \quad \text{if and only if} \quad V_j < (1-\phi)g.$$

For each $j \in \{NN, EN, EA\}$ there exists a unique threshold ϕ_1^j such that $w^{BL\text{-}j*} = w^{BS\text{-}j*}$ at $\phi = \phi_1^j$. If $\phi_1^j \in (0,1)$, then

$$w^{BL\text{-}j*} < w^{BS\text{-}j*} \text{ for } 0 < \phi < \phi_1^j, \qquad w^{BL\text{-}j*} > w^{BS\text{-}j*} \text{ for } \phi_1^j < \phi < 1.$$

If $\phi_1^j \leq 0$, then $w^{BL\text{-}j*} > w^{BS\text{-}j*}$ for all $\phi \in (0,1)$, whereas if $\phi_1^j \geq 1$, then $w^{BL\text{-}j*} < w^{BS\text{-}j*}$ for all $\phi \in (0,1)$. This proves Proposition 4(a).

(b) **Comparison of consumers' total cost and demand**

In the BS model, consumers pay the retail price p_v. From Table 2,

$$p_v^{BS\text{-}j*} = \frac{3a + bc_n}{4b}, \qquad q_v^{BS\text{-}j*} = \frac{a - bc_n}{4}, \qquad j \in \{NN, EN, EA\}. \tag{C.13}$$

In the BL model, consumers pay the bundled access price p_t. From Appendix A.3,

$$p_t^{BL\text{-}j*} = \frac{3a + b\big[c_n - (1-\phi)g - V_j\big]}{4b}, \qquad q_v^{BL\text{-}j*} = \frac{a - b\big[c_n - (1-\phi)g - V_j\big]}{4}. \tag{C.14}$$

The price difference between the two models is

$$p_v^{BS\text{-}j*} - p_t^{BL\text{-}j*} = \frac{1}{4}\big[(1-\phi)g + V_j\big]. \tag{C.15}$$

Under the feasibility conditions in Appendix A.1, $(1-\phi)g + V_j > 0$ for all j, so

$$p_t^{BL\text{-}j*} < p_v^{BS\text{-}j*}.$$

Similarly, the demand difference is

$$q_v^{BL\text{-}j*} - q_v^{BS\text{-}j*} = \frac{b}{4}\big[(1-\phi)g + V_j\big] > 0. \tag{C.16}$$

Hence, relative to the BS model, the BL model strictly lowers consumers' total cost and increases equilibrium EV demand, proving Proposition 4(b).

C.5. Proof of Proposition 5

Let $A := a - bc_n$ and recall that $V_j > 0$ under the feasibility conditions.

(a) EV manufacturer.
From Tables 2 and 3, the EV manufacturer's equilibrium profits under the BS and BL models can be written, for any $j \in \{NN, EN, EA\}$, as

$$\Pi_m^{BS\text{-}j*} = \frac{A^2 + 4b\theta V_j^2}{16b}, \qquad \Pi_m^{BL\text{-}j*} = \frac{\big[A + b\big((1-\phi)g + V_j\big)\big]^2}{16b},$$

where $V_{NN} = \phi g$ and V_{EN}, V_{EA} are defined in Appendix A.1.
Taking the difference gives

$$\Pi_m^{BL\text{-}j*} - \Pi_m^{BS\text{-}j*} = \frac{1}{16}\Big[2A\big((1-\phi)g + V_j\big) + b\big((1-\phi)g + V_j\big)^2 - 4\theta V_j^2\Big]. \tag{C.17}$$

Hence

$$\Pi_m^{BL\text{-}j*} < \Pi_m^{BS\text{-}j*} \quad \text{whenever} \quad \theta > \frac{2A\big((1-\phi)g + V_j\big) + b\big((1-\phi)g + V_j\big)^2}{4V_j^2}. \tag{C.18}$$

(b) Battery supplier.
From Tables 2 and 3, the battery supplier's equilibrium profits under the BS and BL models can be written, for any $j \in \{NN, EN, EA\}$, as

$$\Pi_s^{BS\text{-}j*} = \frac{A^2 + 4b\theta(1-\phi)V_j g}{8b}, \qquad \Pi_s^{BL\text{-}j*} = \frac{\big[A + b\big((1-\phi)g + V_j\big)\big]^2}{8b},$$

where V_{NN}, V_{EN} and V_{EA} are defined in Appendix A.1.
Taking the difference yields

$$\Pi_s^{BL\text{-}j*} - \Pi_s^{BS\text{-}j*} = \frac{1}{8}\Big[2A\big((1-\phi)g + V_j\big) + b\big((1-\phi)g + V_j\big)^2 - 4\theta(1-\phi)V_j g\Big]. \tag{C.19}$$

Under $V_j > 0$ and $\phi \in (0,1)$, this implies

$$\Pi_s^{BL\text{-}j*} < \Pi_s^{BS\text{-}j*} \quad \text{whenever} \quad \theta > \frac{2A\big((1-\phi)g + V_j\big) + b\big((1-\phi)g + V_j\big)^2}{4(1-\phi)V_j g}. \tag{C.20}$$

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