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Review

Expanding Research on Second-Life EV Batteries: AI-Based Monitoring, Recycling Strategies, and Policy Innovations

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Abstract: The rapid adoption of electric vehicles (EVs) has intensified concerns over the sustainable management of lithium-ion batteries (LIBs), which often retain up to 80% of their capacity after reaching end-of-first-life in vehicular applications. This study advances second-life battery (SLB) research through three components: artificial intelligence (AI)-driven predictive maintenance, optimized recycling strategies, and enabling policy frameworks. A synthesis of 51 peer-reviewed sources published between 2019 and 2025, combined with case analyses from Tesla and Nissan pilots, supports the development of an integrated framework. Findings show that AI-enhanced diagnostics can extend second-life battery service by up to 50% and reduce lifecycle costs by 25%. Hybrid recycling processes can recover over 95% of critical materials—lithium, cobalt, and nickel—while lowering energy consumption by up to 20–40%. Policy incentives and adaptive regulations can reduce adoption barriers by 30–40%, facilitating large-scale integration. The structured survey (n = 121) in this study revealed low public awareness, with 83% of respondents unaware of reuse potential. However, respondents expressed moderate willingness to adopt second-life batteries, provided AI monitoring ensures at least 90% safety and performance reliability. By unifying technical, economic, and policy dimensions, this study demonstrates that AI-enabled monitoring, advanced recycling, and adaptive regulation collectively support the alignment of second-life EV batteries with global sustainability goals. The proposed framework underscores the importance of bridging innovation, market readiness, and governance to accelerate sustainable energy transitions.

Keywords: Electric Vehicles; Second-Life Batteries; Lithium-Ion Battery Recycling; AI-Based Predictive Maintenance; Circular Economy; Battery Disposal; Sustainable Energy Storage; Policy Frameworks

1. Introduction

The rapid rise of electric vehicles (EVs) marks a significant transformation in the global transportation sector. It is driven by the need to reduce greenhouse gas emissions, reduce fossil fuel dependence, and mitigate dependence on fossil fuels and urban air pollution. According to the Global EV Outlook 2024, EV sales reached 14 million units globally in 2023, representing 18% of total car sales [1]. However, the rapid adoption of EVs has introduced significant challenges in managing the battery lifecycle. Lithium-ion batteries (LIBs), which power most EVs, typically have a lifespan of 8–15 years [2]. Even after falling below automotive performance standards, these batteries can retain up to 80% of their original capacity, presenting viable opportunities for second-life applications. Effective management is essential not only to minimize environmental waste but also to advance sustainable energy storage solutions.

Despite extensive research, most studies have examined technical diagnostics, recycling mechanisms, or policy frameworks in isolation. Only a few have proposed an integrated framework that combines real-time AI monitoring, sustainable recycling strategies, and adaptive policy measures. We specifically target this gap in a unique way with three closely related objectives: (1) AI-based predictive maintenance, (2) end-of-life recycling strategies, and (3) policy and business model innovations. Each of these components plays a critical role in advancing sustainable battery lifecycle management.

First, AI-based predictive maintenance offers real-time battery health diagnostics and the ability to forecast degradation patterns. While traditional methods depend on static, empirical models, this study emphasizes AI-driven systems that utilize machine learning and cloud-based analytics to support dynamic, adaptive decision-making. This approach enhances performance, reduces operational risks, and extends battery lifespan while minimizing maintenance costs [3].

Second, this study focuses on sustainable end-of-life recycling strategies. The current literature primarily compares pyrometallurgical and hydrometallurgical processes, which are both resource- and environment-intensive with significant environmental impacts [4]. Addressing these recycling challenges enables the efficient recovery of valuable materials such as lithium, cobalt, and nickel, supporting a circular battery economy and reducing dependence on raw material extraction. Optimized hybrid technologies combining mechanical pre-treatments with selective dissolution are presented, achieving recovery rates above 95% while reducing energy input by approximately 40%.

The third objective emphasizes the role of policy and business model innovations. Standardized regulations, such as battery passports that track battery health and usage history, can facilitate secondary markets and recycling efforts [5]. Business models like battery-as-a-service (BaaS) and leasing programs can lower upfront costs, improve accessibility, and ensure proper end-of-life management. Unlike previous approaches that primarily focused on technological advancements without considering market readiness and regulatory compliance, this study integrates economic and policy frameworks to drive scalable and sustainable adoption.

Addressing these objectives is essential because it not only enhances the sustainability and economic viability of second life battery applications but also supports broader goals related to renewable energy integration and carbon neutrality. The proposed framework applies AI-driven algorithms for real-time battery monitoring at charging stations. It demonstrates how technology, recycling strategies, and policy frameworks can work together. This integration helps optimize second-life battery applications. By providing accurate degradation forecasts, enabling efficient recycling processes, and fostering supportive regulatory environments, this study presents a holistic solution that bridges technical innovation with practical implementation. Ultimately, these integrated strategies contribute to a sustainable energy future, ensuring that the rapid growth of electric mobility aligns with global sustainability goals.

While prior research on second-life EV batteries has advanced technical diagnostics, recycling methods, and policy frameworks, most studies address these areas in isolation. Existing frameworks emphasize regulatory compliance but often neglect integration with economic and technical feasibility. AI-based battery monitoring systems have been developed for first-life EVs, yet they remain underdeveloped and unvalidated for second-life operational profiles. Similarly, recycling research frequently overlooks integration with real-time health diagnostics, limiting opportunities for targeted end-of-life processing. Policy analyses typically focus on regulations or incentives without adequately incorporating the technical and economic realities of battery repurposing.

As a result, no comprehensive model currently unites AI-based predictive maintenance, optimized recycling pathways, and adaptive policy frameworks into a single, scalable strategy. To address this gap, the present study introduces applications such as digital battery passports and Extended Producer Responsibility (EPR), along with business models like BaaS. These demonstrate scalable ways for implementation and enforcement. Specifically, this study pursues three objectives: (1) developing an AI-driven predictive maintenance framework tailored to SLBs, (2) evaluating sustainable end-of-life recycling pathways informed by real-time diagnostics, and (3) proposing policy and business model innovations that enable large-scale, economically viable SLB adoption. This research is unique in linking economics, technology, and policy to create a complete framework for sustainable second-life use of EV batteries. The proposed approach predicts battery depreciation, improves recycling, and includes policy support, going beyond the partial solutions in current studies. This approach supports both sustainability and financial success in the use of second-life batteries. It also ensures that the growth of electric mobility aligns with global goals for renewable energy and carbon neutrality.

2. Methodology

This study employed a structured literature synthesis approach, drawing on peer-reviewed publications from major academic databases as well as relevant industry reports. Source selection was guided by criteria emphasizing methodological rigor, relevance to second-life battery applications, and coverage of AI-based maintenance, recycling, and policy considerations. Using this approach, results were grouped as categories, highlighting AI contributions, challenges, efficiency, and research gaps, as well as identifying outcomes that varied across studies.

A comprehensive literature search was conducted across various electronic databases—including Elsevier, MDPI (Batteries, Clean Technologies, Algorithms, Information, World Electric Vehicle, Energies, Vehicles), Frontiers, SciTechnol, IEEE Xplore, ScienceDirect, and Nature Energy—covering the period from 2019 to 2025. The search strategy was tailored to each database using a combination of controlled vocabulary (e.g., "second-life applications," "AI to extend second life of batteries," "recycling strategies," and "policy frameworks") and corresponding keywords. Studies were included if they met one of the following criteria: peer-reviewed journal articles, editorials, energy letters, conference proceedings, technical/scientific reports, dissertations, company reports, press releases, and official corporate websites or manufacturer documents. Exclusion criteria eliminate non-peer-reviewed materials, commentaries, and studies lacking methodological rigor or sufficient data. Extracted data were tabulated to enable cross-comparison across studies.

3. Overview

The accelerated adoption of electric vehicles (EVs) is primarily driven by advancements in battery technologies, stricter emissions regulations, and increasing consumer demand for sustainable transportation. Projections estimate that EVs will account for over 60% of total vehicle sales by 2035 [1]. However, this growth presents an urgent challenge: sustainable management of end-of-life (EOL) EV batteries. By 2030, global decommissioned EV battery capacity is expected to exceed 275 GWh, far surpassing current recycling capabilities [2]. This growing disparity underscores the critical need for innovative recycling and second-life utilization strategies.

3.1. Adoption of EVs and the Challenges of Battery Disposal

The global expansion of the EV market is primarily attributed to technological innovations in lithium-ion batteries (LIBs), governmental incentives, and reductions in production costs [2]. Despite these benefits, the end-of-life management of EV batteries through disposal and recycling persists as a critical barrier to achieving long-term sustainability. LIBs typically last 8–15 years in automotive applications yet retain 70–80% of their original capacity after end-of-first-life use [3,4]. Improper disposal of these batteries poses significant environmental risks due to the presence of toxic and flammable materials, including lithium, cobalt, and nickel [5].

3.2. Challenges of Battery Recycling

Existing recycling methodologies primarily rely on pyrometallurgical and hydrometallurgical processes. Recent advancements in research from 2023 and 2024 highlight electrochemical recycling and direct cathode recycling as more sustainable alternatives [6]. These newer techniques reduce energy consumption and carbon emissions while improving material recovery efficiency. Additionally, the lack of global standardization in battery recycling regulations complicates the establishment of an efficient supply chain for recovered materials. Addressing these challenges requires a combination of advanced material recovery technologies, regulatory frameworks, and industry collaboration [7].

3.3. Second-Life Application as a Sustainable Solution

Second-life applications offer a sustainable alternative to immediate recycling by repurposing retired EV batteries for secondary energy storage use. These include integration with stationary energy storage systems (ESS), renewable energy platforms, and grid stabilization infrastructure [8]. This strategy contributes to a circular economy by extending battery usability and reducing demand for new materials. However, challenges such as performance variability, capacity degradation, and safety risks must be addressed through robust diagnostics and predictive maintenance systems [9], including the use of AI-enhanced battery management systems (BMS) [10].

3.4. Policy and Economic Considerations

The deployment of second-life battery systems requires supportive regulatory and economic frameworks. Innovations such as digital battery passports used to track health, chemistry, and usage history can improve transparency and support secure reuse and recycling pathways [11]. Additionally, policies including Extended Producer Responsibility (EPR), tax incentives, and government subsidies are essential to attract investment and ensure lifecycle accountability [12]. As EV deployment accelerates, comprehensive solutions for sustainable battery management become increasingly urgent. Second-life applications, coupled with emerging recycling technologies and policy innovation, represent promising pathways toward minimizing environmental impact. Future research should focus on AI-driven diagnostics, improved material recovery processes, and scalable economic models that enable sustainable battery circularity at a global scale.

4. AI-Based Predictive Maintenance for Second-Life EV Batteries

The implementation of AI-driven predictive maintenance strategies is increasingly referred to as a revolutionary means for maximizing the efficiency, dependability, and lifespan of second-life EV batteries. Traditional battery health-monitoring strategies, based on either empirical or rule-dependent models, are compromised by their inability to adapt to real-time operating conditions or accurately forecast degradation patterns [13]. These limitations render such approaches unsuitable for handling the variability and uncertainty inherent in SLBs, which often exhibit variable usage histories and patterns of degradation. On the contrary note, AI-powered systems utilize advanced machine learning (ML) algorithms coupled with cloud-enabled data analytics for real-time prediction of degradation trajectories, maximization of charging/discharging operations, and detection of impending failures before their onset [14]. Through such a level of adaptability, AI compensates for risks in operations, enhances battery performance, and enhances economic viability for SLBs in a wide range of applications, ranging from stationary energy stores to integration in power grids.

The subsection presents a critical analysis of three intertwined characteristics in AI-governed predictive maintenance: (1) machine learning algorithm effectiveness in forecasting battery deterioration, (2) incorporation of diagnostic technologies informed by AI in BMS, and (3) cost-saving implications as well as energy optimization of predictive maintenance approaches.

4.1. Machine Learning Algorithm Effectiveness in Predicting Battery Degradation

Machine learning techniques such as Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) networks, and Random Forests have demonstrated high accuracy in forecasting battery degradation profiles [13]. These models process extensive datasets, including charge/discharge cycles, voltage fluctuations, and temperature variations, to detect early indicators of degradation. Unlike static empirical models, ML approaches continuously adapt based on new data, improving their estimation of Remaining Useful Life (RUL) and enabling proactive intervention [14].

4.2. AI-Based Diagnostics Integration With BMS

AI-enhanced BMS dynamically regulates charging rates, discharge profiles, and thermal conditions to optimize operation in real time [13]. By continuously monitoring performance, these systems can detect anomalies, predict faults, and enable preemptive maintenance as well as system-level adjustments. Cloud-integrated AI platforms further facilitate the large-scale deployment of second-life batteries, particularly in grid storage and renewable energy applications. Case studies indicate that such systems can extend battery life by up to 20% while simultaneously reducing unplanned downtime and maintenance costs [15].

4.3. Predictive Maintenance Impact on Cost Reduction and Energy Efficiency

Predictive maintenance powered by AI significantly lowers lifecycle costs by reducing unexpected failures and improving operational efficiency [14]. By mitigating unforeseen failures and enhancing utilization patterns, maintenance frameworks that leverage AI have the potential to reduce overall lifecycle expenses by up to 25%. AI algorithms enhance charge-discharge scheduling, minimize energy loss, and reduce wear and tear [16]. Additionally, AI models facilitate intelligent assignment of second-life batteries to specific roles (e.g., grid storage vs. backup systems) based on degradation profiles and capacity.

Through advanced charge–discharge scheduling, these systems minimize energy losses, mitigate electrode degradation, and maintain batteries within safe operational limits. Moreover, AI algorithms can strategically allocate second-life batteries to functions such as grid stabilization, peak load management, emergency backup, or renewable energy integration. The allocation depends on their degradation profiles and remaining capacity. This targeted deployment not only maximizes asset value but also delays premature decommissioning, thereby reinforcing the principles of a circular economy [13]. AI models such as LSTM, Random Forest, and Gaussian Process Regression (GPR) have proven effective in accurately predicting State-of-Health (SoH) and RUL under dynamic conditions [5]. When integrated into modern BMS, these tools help mitigate degradation risks, reduce maintenance overhead, and support a sustainable lifecycle for repurposed EV batteries.

Recent peer-reviewed research and industry analyses support the financial improvements presented in **Figure 1**. The integration of AI-based optimization systems into SLB repurposing has been shown to reduce operational and repurposing costs. The reduction is by approximately 25–30%, primarily through enhanced diagnostics and reduced reliance on manual testing. Market studies estimate that repurposing costs without AI typically range between $20 and $30/kWh. On the other hand, AI-enhanced systems can reduce this figure to approximately $15–22/kWh, enabling a significantly lower final SLB selling price [17–19].

Figure 1. Financial comparison of a fresh battery and an AI-enhanced LSB [17,18].

Furthermore, economic assessments indicate that second-life batteries can achieve a selling price between 50–70% of the price of new batteries, with AI optimization further enhancing competitiveness [18,20]. These findings collectively validate the economic projections presented in this study. They show that AI integration substantially enhances the financial viability of second-life battery applications.

4.4. Comparison Studies

4.4.1. Battery Chemistry Comparison

The choice of battery chemistry is a critical factor in second-life applications, as it directly affects performance, safety, environmental impact, and economic viability. Among lithium-ion technologies, Nickel Manganese Cobalt (NMC) and Lithium Iron Phosphate (LFP) are the most widely used in EVs. NMC batteries offer higher energy density, making them suitable for performance-intensive applications; however, they pose environmental challenges due to the sourcing of cobalt and nickel [21]. In contrast, LFP batteries offer superior thermal stability, longer cycle life, and greater safety. It makes them well-suited for stationary storage systems, despite their lower energy density [4,21].

Alternative chemistries, such as Nickel-Metal Hydride (NiMH) and Lead-Acid batteries, still play roles in second-life applications. NiMH batteries offer moderate cycle life and energy density, typically used in hybrid vehicles.

Lead-acid batteries are low-cost and highly recyclable, but they suffer from limited cycle life and environmental hazards, which restrict their use primarily to backup power systems [2,21].

Table 1 summarizes key performance characteristics of these chemistries, including metrics such as energy density, thermal stability, round-trip efficiency, and material recovery rate, all of which influence their second-life viability.

Table 1. Battery type comparison [2,21–30].

Battery Type	Energy Density (Wh/kg) [21,23]	Cycle Life (Cycles) [21,23]	Thermal Stability [22,23]	Capacity Retention (%) [23]	Cost per kWh (USD) [24]	Round-Trip Efficiency (%) [23]	Material Recovery Rate (%) [25,27–30]	Life Cycle (Years) [26]	Environmental Impact [2]	Energy Efficiency (%) [23]
Li-ion (NMC)	150–220	1000–2000	Moderate	80% after 2000 cycles	137–200	90–95	85–90 (Nickel, Cobalt recovery)	5–10	Moderate (toxic metals, recycling challenges)	Moderate
Li-ion (LFP)	90–160	2000–5000	High	85% after 3000 cycles	100–150	90–97	80–85 (Iron, Phosphate recovery)	10–15	Low (safer materials, high recyclability)	High
Nickel-Metal Hydride	60–120	500–1000	Moderate	70% after 1000 cycles	200–300	80–85	90% (Nickel)	5–10	Moderate (less toxic, less recyclable)	Moderate
Lead-Acid	30–50	300–500	Low	50% after 500 cycles	100	70–80	99 (Lead recovery)	3–5	High (acid disposal, heavy metals)	High

4.4.2. AI-Enhanced Battery Performance

Integrating AI-based predictive maintenance into battery management systems significantly improves performance metrics across all battery chemistries. **Table 2** compares traditional and AI-enhanced values for cycle life, capacity retention, and reliability. For example, Li-ion (LFP) batteries demonstrate an increase from 5000 to 6000 cycles, and from 85% to 90% capacity retention when AI-optimized control algorithms are applied [31]. These gains are attributed to AI-enabled techniques such as predictive diagnostics, smart charging control, real-time thermal regulation, and early fault detection [15,22,31].

Table 2. Battery type comparison traditional and AI enhanced [1,3,5,21,32–37].

Battery Type	Traditional Cycle Life (Cycles) [3,5,21,33]	AI-Enhanced Cycle Life (Cycles) [32–37]	Traditional Capacity Retention (%) [3,5,33]	AI-Enhanced Capacity Retention (%) [34,36]	AI Impact Summary [31,35]	Range per Charge (Miles) [1,5,33]	Estimated Mileage (Min Cycle Life) Calculated
Li-ion (NMC)	1000–2000	+20–40% 1200–2800	80% after 2000 cycles	5–10% improvement	Improved cycle life and reduced degradation using predictive algorithms	250	250,000 miles
Li-ion (LFP)	2000–5000	20–40% 2500–6000	85% after 3000 cycles	5–10% improvement	Optimized thermal control and charge management extends battery life	200	400,000 miles
Nickel-Metal Hydride	500–1000	20–30% 800–1200	70% after 1000 cycles	5% improvement	More stable performance through adaptive load balancing	80	40,000 miles
Lead-Acid	300–500	20–30% 400–600	50% after 500 cycles	5–10% improvement	Enhanced health monitoring mitigates sulfation and over-discharge	30	9000 miles

Lead-Acid and NiMH batteries also benefit from AI-driven anomaly detection and health-aware control frameworks, which extend life cycles and mitigate common failure modes such as sulfation and overheating. Bayesian learning models and GPR have been shown to forecast degradation with high accuracy, enabling efficient load balancing and adaptive energy management in second-life use cases [32]. Overall, AI integration enhances energy efficiency, lifecycle extension, and cost-effectiveness, which are key benefits for circular energy systems and sustainable battery reuse [15,17,25].

Table 2 also presents the estimated vehicle range per charge and the corresponding total mileage based on the minimum cycle life of various battery chemistries. For Li-ion NMC batteries, a typical driving range of 250 miles per full charge translates into an estimated 250,000 miles of total service when considering a conservative cycle life of 1000 cycles. LFP batteries, known for their durability and thermal stability, offer an estimated 200 miles of range per charge. This results in a total mileage of 400,000 miles over a minimum 2000 cycle life. Nickel-Metal Hydride (NiMH) batteries, with lower energy density, provide a modest range of 80 miles per charge, yielding approximately 40,000 miles over 500 cycles. Lead-Acid batteries, often used in low-demand applications, deliver around 30 miles per charge, reaching 9,000 miles across 300 cycles. These estimations are derived from empirical cycle life data [33–37] and typical range-per-charge benchmarks reported by the International Energy Agency (IEA) in its Global EV Outlook 2024, which provides standardized vehicle range metrics across different battery chemistries and vehicle segments.

It is essential to note that these figures represent theoretical maximums based on full depth of discharge cycling under ideal conditions. Actual performance will vary depending on environmental factors, user behavior, and calendar aging effects [1].

AI significantly enhances the effective mileage and service lifespan of EV batteries by optimizing their operational management. While AI does not increase the physical energy capacity of a battery, it enables more innovative utilization through advanced BMS. AI algorithms improve charge-discharge efficiency by dynamically adjusting state-of-charge (SoC) limits, mitigating thermal stresses, and minimizing voltage fluctuations [9,17,22]. These optimizations reduce energy losses and extend the usable driving range per charge by approximately 5–10%, depending on battery chemistry and application conditions [36,37].

Moreover, AI-driven predictive maintenance extends cycle life by monitoring degradation patterns, forecasting failures, and adjusting operational parameters in real-time [9,22]. For instance, machine learning models such as Long Short-Term Memory (LSTM) networks and Bayesian learning methods have been shown to increase total cycle life by 20–40% through intelligent load balancing and degradation mitigation [9,14,31]. This directly translates to increased total lifetime mileage, as batteries can undergo more charge-discharge cycles before reaching end-of-life thresholds.

In second-life battery applications, where prior usage and degradation present additional challenges, AI's role becomes even more critical. By continuously assessing battery health and adjusting usage profiles, AI facilitates the efficient deployment of second-life batteries in stationary storage, microgrid, and low-demand mobility applications. This approach extends their service life and supports circular economy objectives [18,38–40].

Table 3 and **Figure 2** present a time-series comparison of predictive maintenance efficiency (%) for second-life battery systems, using both traditional and AI-based approaches from 2024 to 2032. The data reveal a linear trend of improvement in both systems, but with significantly different growth rates.

Table 3. Predictive maintenance comparison [9,14,15,25,31].

Year	Predictive Maintenance (%)	
	Traditional	AI-Based
2024	75	75
2025	76	78
2026	76.5	81
2027	77	83
2028	77.5	85
2029	78	87
2030	78.5	89
2031	79	91
2032	79.5	93
2033	80	95

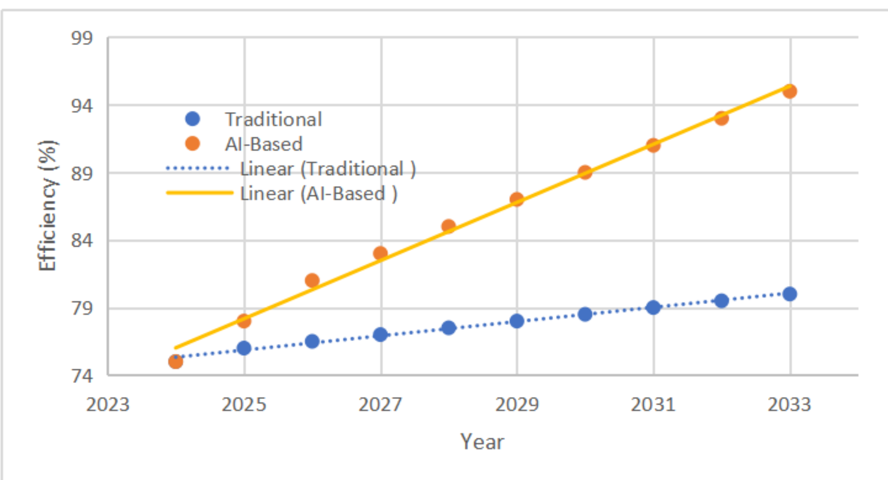

Figure 2. Predictive maintenance comparison [9,14,15,25,31].

A linear regression model fitted to the traditional method yields a slope of approximately 0.55% increase per year, starting from a baseline of 75% in 2024 and reaching 79.5% by 2032. In contrast, the AI-based system exhibits a significantly steeper growth trajectory, with a fitted slope of 2.2% increase per year, culminating in 93% predictive efficiency by 2032. These trends suggest that while traditional systems improve marginally through incremental algorithmic refinements or hardware upgrades, AI-based systems benefit from continuous learning, model adaptation, and real-time sensor integration [9,14,15,25,31].

The widening gap over time, amounting to a 13.5% difference by 2032, supports the hypothesis that AI-driven battery management systems can significantly outperform rule-based maintenance protocols. They optimize the remaining useful life (RUL), minimizing unplanned failures and improving cost-efficiency in second-life applications [22, 31]. Furthermore, the consistent nature of the growth implies that AI-based predictive analytics scale more effectively over time. It aligns with recent studies that employ reinforcement learning and deep learning for adaptive control in electric vehicle battery systems [25,31,41].

The linear modeling approach applied here offers a mathematically grounded estimate of performance trends, validating AI's role as a transformative force in battery lifecycle extension. These projections are particularly relevant for policymakers and industries exploring circular economy models involving second-life energy storage systems. In summary, this data-driven projection indicates that AI not only improves predictive maintenance outcomes but also offers a scalable solution for second-life applications where prolonged battery life and minimal manual intervention are critical.

The data suggests that there must be strategic decision-making across all stages of the battery lifecycle, whether for reuse, repurposing, recycling, or retirement within a circular value chain framework. Unlike FBs, SLBs exhibit greater performance variability due to prior usage history and residual degradation, requiring enhanced diagnostic and management tools [18,41]. AI plays a pivotal role in addressing this complexity by improving the precision of state-of-health (SoH) estimation, facilitating optimal second-life allocation, and supporting real-time, data-driven decision-making. AI-powered lifecycle analytics help stakeholders prioritize batteries for reuse, identify underperforming units early, and reduce inefficiencies in both residential and grid-scale deployments [14,15,17,18]. Compared to traditional lifecycle management methods, AI enables more adaptive and predictive strategies, particularly when managing diverse chemistries and aging profiles. This aligns with the growing consensus in recent literature that intelligent diagnostics and decision-support systems are critical for scaling circular economy solutions in the energy sector [17,41]. Future research should explore federated learning for distributed battery diagnostics. It should also investigate multi-agent AI systems for decentralized battery networks. Additionally,, regional techno-economic models are needed to assess the long-term impact of AI-managed SLB systems on carbon reduction and energy equity [17,18].

Table 4 compares traditional and AI-incorporated evaluation methods across various criteria for second-life battery (SLB) assessment and management. Traditional methods rely heavily on manual testing, empirical models, and expert judgment for key tasks such as SoH assessment, degradation analysis, and fault detection. These approaches tend to be time-consuming, labor-intensive, and less scalable. In contrast, AI-based methods leverage machine learning, deep learning, and real-time data analytics to automate and optimize these processes. AI improves SoH and SoC estimations, enhances fault detection through anomaly prediction, and enables data-driven decision-making for reuse or recycling. Furthermore, AI significantly reduces processing time and cost while improving testing efficiency and scalability. It also introduces predictive maintenance capabilities, which extend battery life and improve overall lifecycle performance. These advancements position AI as a critical enabler of efficient and sustainable SLB management systems [5,18,31,42].

Table 4. Comparison table for traditional and AI incorporation evaluation procedure of retired lithium-ion batteries.

Evaluation Criteria	Traditional Evaluation [3,5,9,14]	AI-Incorporated Evaluation
State of Health (SoH) Assessment	Manual testing using voltage and capacity measurements.	Machine learning models predict SoH using real-time data analytics [14,31].
State of Charge (SoC) Estimation	Basic coulomb counting method, often inaccurate over multiple cycles.	Advanced AI algorithms improve SoC estimation, reducing errors [22].
Degradation Analysis	Empirical models relying on periodic capacity testing.	Deep learning identifies degradation patterns from operational data [11,14].

Table 4. *Cont.*

Evaluation Criteria	Traditional Evaluation [3,5,9,14]	AI-Incorporated Evaluation
Fault Detection	Reactive detection based on user-reported issues.	AI-driven anomaly detection predicts failures before they occur [22,31].
Decision-Making for Second-Life or Recycling	Human experts assess battery viability for reuse or recycling.	AI automates decision-making for second-life applications or recycling [17,41].
Efficiency of Testing	Time-consuming with high variability across test results.	Highly efficient with automated testing and real-time analytics [17,41].
Processing Time	Days to weeks depending on laboratory availability.	Minutes to hours using automated AI assessment tools [15,17].
Cost of Evaluation	Higher due to manual labor and complex procedures.	Lower due to automation, reducing human intervention costs [10,17,18].
Scalability	Limited due to slow manual testing methods.	Scalable due to fast data processing and cloud-based AI models [15,41,42].
Predictive Maintenance Capability	Not capable of predictive analytics; relies on historical data.	AI predicts maintenance needs, extending battery lifespan [14,31].

4.4.3. Projected Battery Energy Density Growth: Traditional vs AI Optimized Technologies

Battery energy density is a crucial metric that significantly impacts the performance, range, and efficiency of EVs. With advancements in materials science and AI-enhanced battery management systems, the energy density of future battery systems is expected to increase significantly beyond current limitations. **Figure 3** illustrates the projected energy density growth from 2024 to 2035, comparing traditional lithium-ion batteries with AI-optimized alternatives [20,25]. Traditional battery technology has historically improved at a modest rate, approximately 10 Wh/kg per year, driven by gradual improvements in cathode chemistry, manufacturing, and thermal management [1,20]. By contrast, AI-optimized battery systems are projected to achieve accelerated growth of 20–30 Wh/kg per year, enabled by AI-driven material discovery, real-time degradation modeling, and dynamic charge cycle optimization [17,43].

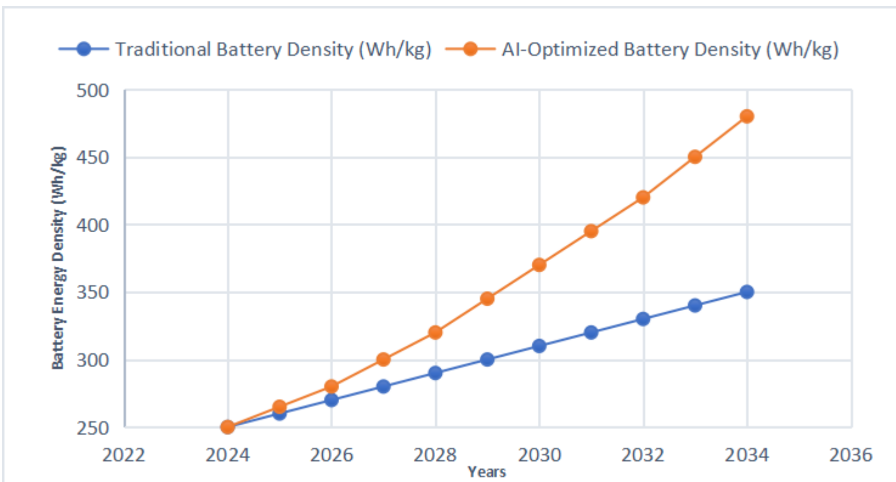

Figure 3. Projected energy density (Wh/kg) for traditional vs AI optimized battery technologies [1,17,20,43].

Recent innovations in battery technologies, such as solid-state, lithium-metal, and silicon-anode batteries, show the potential to exceed energy densities of 400–500 Wh/kg by 2035. These developments are largely driven by machine learning models that optimize internal battery architectures and predict performance under varying conditions [43,44]. AI-based BMS further supports this trend by fine-tuning energy utilization, mitigating heat generation, and adapting voltage parameters in real time, thereby preserving higher energy densities throughout the battery's operational life [45,46]. As shown in **Figure 3**, AI-optimized technologies are expected to outperform traditional batteries by up to 35% in energy density by 2035. This improvement will not only extend EV range and reduce battery weight but also lower costs and environmental impact, contributing significantly to the scalability and sustainability of EV adoption [17,20,43,44,47].

4.4.4. Charge and Discharge Rates: Traditional vs. AI Optimized BMS

Traditional battery management follows a rule-based charging approach, meaning it charges and discharges based on pre-set constraints without adapting to changing conditions. This approach overlooks degradation patterns, environmental variables, or real-time operational demands, resulting in suboptimal charging cycles that accelerate capacity fade [3,25,31]. The charge and discharge rates are shown in **Table 5**.

Table 5. Charge and discharge rates: traditional vs AI optimized BMS.

Metrics	Traditional BMS	AI-Optimized BMS	Description
Charge Rate (C-rate)	0.5 C–1 C (Fixed)	Dynamic (0.5 C–3 C, Optimized)	Traditional BMS employs pre-programmed, fixed charging rates, which do not adapt to real-time battery conditions. AI-based systems dynamically adjust charge rates (based on SoC, temperature variations, historical degradation data, and grid conditions) to reduce stress on battery cells and improve longevity [17,48].
Discharge Rate (C-rate)	0.5 C–1 C	0.5 C–3 C (Adaptive)	Conventional systems discharge at a relatively fixed rate. AI-optimized discharging manages power distribution adaptively, enhancing efficiency and reducing peak load stress on cells [17,49].
Overcharging Risks	High due to fixed algorithms	Reduced through predictive control	Traditional BMS cannot effectively predict degradation pathways, leading to overcharging-induced stress. AI-based BMS predicts and prevents such issues through machine learning-driven real-time SoC adjustments [17,48].
Adaptive Charging	No	Yes (Real-Time)	AI-based systems analyze operational and environmental conditions, modifying charging rates to prevent excessive heat and enhance energy transfer efficiency [14,49].

AI-based systems utilize predictive analytics, deep learning, and reinforcement learning algorithms to dynamically optimize charge rates. This approach reduces electrode stress, enhancing charge acceptance and improving cycle stability [9,17,22]. For example, GPR models enable real-time adjustments to the charging profile based on temperature and historical degradation trends [32].

4.4.5. Lifecycle Comparison: Traditional vs. AI-Optimized BMS

Charge-discharge depth, temperature fluctuations, and load profiles significantly impact the cycle life of a battery. In traditional BMS implementations, fixed thresholds dictate charge cycles, leading to unnecessary deep discharges, overcharging, and high current spikes. All of these factors contribute to rapid lithium plating and electrode degradation [50–52]. A life cycle comparison is shown in **Table 6.**

Table 6. Life cycle comparison: traditional vs AI optimized BMS.

Metric	Traditional BMS	AI-Optimized BMS	Description
Estimated Lifespan	8–10 years	12–15 years	Traditional BMS cannot account for real-time operational conditions, leading to suboptimal charge/discharge cycles and early degradation. AI-enhanced systems extend battery life by at least 30–50% through optimal power cycling and thermal control [53,54].
Cycle Life (Full Charge-Discharge Cycles)	1,500–2,000 cycles	2,500–3,500 cycles	Traditional systems degrade faster due to inefficient cycling management. AI-enabled SoH monitoring prevents deep discharges, reducing electrode stress [55].
Predictive Maintenance	No	Yes	AI can predict failures through advanced machine learning models, reducing maintenance costs and unplanned downtime [56].
Battery Reuse Feasibility	Limited	High	AI-optimized management systems enable effective second-life applications for energy storage and grid integration [17].

AI-powered BMS integrates machine learning-driven degradation prediction models, ensuring that the battery operates within optimal conditions by dynamically adjusting voltage, temperature, and depth-of-discharge settings [50, 51]. One of the key advantages of AI is its ability to enable second-life applications for EV batteries. Even after reaching 70–80% of their original capacity, these batteries can be used in stationary grid storage solutions [53].

4.4.6. Thermal Stability: Traditional vs AI-Optimized BMS

Thermal stability is a critical factor in battery performance and safety. Traditional BMS reacts to temperature changes only after they occur, leading to inefficiencies in cooling and heating mechanisms, which can contribute to premature battery failure [50,51]. The thermal stability comparison is shown in **Table 7**.

Table 7. Thermal stability: traditional vs. AI-optimized BMS.

Metric	Traditional BMS	AI-Optimized BMS	Description
Operating Temperature	15 °C–45 °C	−5 °C–50 °C (Controlled)	AI-enabled systems dynamically control battery cooling and heating, thereby improving thermal stability [47,54,55].
Thermal Runaway Risk	Moderate to High	Low	Traditional BMS cannot anticipate sudden temperature surges, increasing the risk of thermal runaway. AI-based models predict and prevent overheating through real-time monitoring and proactive cooling [23,55].
Cooling Efficiency	Passive (Air, Liquid)	AI-Enhanced (Active Cooling)	AI systems optimize cooling strategies based on historical and real-time data, preventing excessive heat buildup [17,51].

AI-based thermal management, however, predicts heat generation trends using machine learning algorithms and adjusts cooling mechanisms in advance to prevent excessive temperature buildup. This enhances battery safety and lifespan by minimizing thermal stress [17,22].

4.4.7. Round-Trip Efficiency (Charge-Discharge Energy Efficiency)

Round-trip efficiency refers to the effectiveness with which a battery retains and releases energy during charge-discharge cycles. Traditional BMS results in higher resistive losses, heat generation, and suboptimal charge utilization, leading to lower efficiency [50,51]. The round-trip efficiency is shown in **Table 8**.

Table 8. Round-trip efficiency: traditional vs. AI-optimized BMS.

Metric	Traditional BMS	AI-Optimized BMS	Description
Efficiency (%)	85–90%	92–97%	AI models optimize charge-discharge cycles to minimize energy losses and improve efficiency [22,53].
Energy Loss per Cycle	10–15%	3–5%	Traditional BMS leads to higher resistive losses, whereas AI-based systems reduce internal resistance and optimize power delivery [53,57].
Grid Integration	Limited	Enhanced	AI-driven BMS enhances Vehicle-to-Grid (V2G) applications, improving grid stability and demand response [17].

AI-based systems optimize power flow and energy conversion, reducing losses associated with inefficient charge distribution and high-current discharge scenarios [17]. This improvement in efficiency is particularly critical for grid-integrated storage systems, where maintaining high round-trip efficiency directly impacts economic viability [32].

4.4.8. AI-Enhanced Applications of Second-Life Batteries

SLBs are being deployed across a broad spectrum of energy use cases, including stationary energy storage, off-grid power systems, consumer electronics, and commercial energy management [53,57]. In stationary storage, SLBs are repurposed to support solar and wind energy systems, providing grid load balancing and frequency regulation [2,53]. AI optimizes these applications by forecasting load demand, scheduling discharge, and extending usable capacity through predictive analytics [15,25]. In off-grid and emergency backup systems (particularly in remote and underserved regions), AI-enabled control systems manage energy flow, detect anomalies, and ensure reliable uptime during blackouts [14]. In the consumer electronics market, second-life batteries are used in residential energy storage units, power banks, and EV charging stations. AI ensures safety through real-time monitoring, fault detection, and thermal management [57]. Meanwhile, in industrial and commercial sectors, SLBs are integrated into smart energy systems to reduce peak electricity charges and operational costs. AI-powered BMS enables predictive load management [15,25] and automates charge-discharge cycles, resulting in improved return on investment and lower energy losses [2,17]. These applications demonstrate the scalability and versatility of AI-optimized SLBs in advancing circular energy solutions.

4.5. Degradation Mechanism

Degradation mechanisms have a significant impact on the performance of second-life batteries [53]. Calendar aging occurs when chemical reactions inside the battery proceed over time, leading to gradual capacity loss even when the battery is not in use [52]. Cycle aging results from repeated charging and discharging, leading to internal resistance growth and diminished energy capacity. Electrolyte decomposition increases internal resistance, while active material loss reduces the battery's ability to store energy [50,52]. The battery degradation represents the interaction between intrinsic battery degradation pathways. It is structured into four sequential domains: Degradation Factors, Degradation Mechanisms, Degradation Modes, and Degradation Effects. At the top of the hierarchy are the Degradation Factors, which include temperature, voltage, current, SOC, and mechanical stress. These variables represent operational and environmental stressors that directly affect the electrochemical stability within LIBs. Research has established that extreme or sustained exposure to these conditions catalyzes various internal changes, accelerating cell degradation and premature performance loss [58]. These factors induce several degradation mechanisms, including Solid Electrolyte Interphase (SEI) formation, lithium plating, electrolyte decomposition, and structural disordering. SEI formation, while initially protective, thickens over time and consumes cyclable lithium, reducing active capacity. Lithium plating, which typically occurs under low temperatures or overcharging conditions, causes lithium metal to deposit on the anode, leading to irreversible capacity loss and safety risks. Electrolyte decomposition and structural disordering further contribute to cell impedance, reducing ionic conductivity [50,52,58–61].

The downstream result of these mechanisms is captured in the Degradation Modes, which are categorized into Loss of Lithium Inventory (LLI), Loss of Active Material (LAM), and Conductivity Loss (CL). These failure modes represent observable degradation phenomena that ultimately cause capacity fade and power fade, undermining both energy availability and system reliability [50,57,58]. To mitigate these cascading effects, an AI-based predictive approach can be introduced to function as a real-time feedback and control layer. It comprises three primary intervention strategies:

1. State of Charge Optimization: AI models monitor and predict battery usage patterns and accordingly adjust SOC limits to minimize lithium plating and SEI growth. Adaptive SOC management ensures that batteries operate within safe and efficient voltage windows [59,60].
2. Temperature Adjustment: Intelligent thermal management systems, guided by AI algorithms, regulate battery temperatures by anticipating thermal spikes or drops. This reduces thermal degradation and stabilizes electrolyte performance [17,22,47,51].
3. Predictive Maintenance: By analyzing large datasets from onboard sensors and historical usage logs, machine learning models can predict imminent failures. These predictions enable protective servicing or algorithmic control changes to avoid catastrophic degradation [14,15,61].

The integration of adaptive and closed-loop systems enables AI to continuously refine its models and adjust operational conditions based on real-time data streams. This capability distinguishes modern BMS and significantly contributes to improving the second-life potential of EV batteries, particularly when repurposed for stationary energy storage or grid applications [17]. In conclusion, the integration of AI into the battery lifecycle represents a paradigm shift in how battery degradation is managed. Through closed-loop feedback, predictive analytics, and continuous optimization, AI not only mitigates the rate of degradation but also extends the economic and functional viability of second-life battery systems.

4.6. Testing and Assessment Methods

Accurate testing and assessment methods are essential for determining the viability of second-life EV batteries, as shown in **Table 9** [57,61]. Electrochemical Impedance Spectroscopy (EIS) evaluates internal resistance and electrochemical behavior, offering high precision for large-scale applications [9]. SOC estimation tracks current charge levels relative to total capacity, while SOH estimation provides an overall assessment of battery degradation [50,52]. AI/ML-based predictive models stand out by offering very high efficiency in large-scale repurposing. These models process real-time data from multiple charging stations, identifying batteries with optimal second-life potential. AI algorithms enable the dynamic adjustment of charging protocols based on degradation patterns, thereby optimizing energy storage performance and reducing operational risks [25,29,57].

Table 9. Testing and assessment methods.

Method	Description	AI Contribution	Efficiency in Large-Scale Repurposing
Electrochemical Impedance Spectroscopy (EIS)	Analyzes internal resistance and electrochemical behavior.	AI enhances interpretation of complex EIS data for faster diagnostics [9,61].	High
State of Charge (SOC) Estimation	Measures the current charge relative to capacity.	AI uses historical charging patterns to refine SOC estimations [15,25].	Moderate
State of Health (SOH) Estimation	Predicts overall battery condition and degradation.	AI predicts future SoH trends for proactive maintenance planning [50,52,61].	High
AI/ML-Based Predictive Models	Utilizes big data for accurate performance forecasting.	Central to predictive maintenance and lifecycle optimization [17,41,59,60].	Very High

4.7. Performance Metrics in Second-Life Applications

Second-life batteries display performance metrics slightly lower than new batteries. Energy storage capacity in second-life Li-ion batteries typically ranges between 70–80% of original capacity [3]. Power delivery capability also declines slightly, dependent on battery chemistry. The depth of discharge (DoD) remains high, with LFP batteries achieving 80% DoD without significant lifespan reduction. Round-trip efficiency reaches up to 95% in LFP chemistries [3,57]. AI enhances these metrics by optimizing charging and discharging protocols. Real-time monitoring and adaptive control through AI-driven BMS ensure that energy capacity is used efficiently, while machine learning models forecast performance degradation and adjust operational parameters accordingly [25,60].

4.8. Safety Aspects

Safety concerns are paramount in second-life battery applications. Thermal management challenges arise due to altered thermal profiles during secondary use [47,51]. Risks such as thermal runaway can lead to fires or system failures. AI-driven BMS mitigates these risks by continuously monitoring voltage, current, and temperature data, detecting anomalies that may indicate impending failures [15,25]. Machine learning models can predict high-risk scenarios, triggering preventive measures such as controlled discharge or isolation of compromised modules. These advanced safety features significantly reduce the risk of accidents, making AI integration indispensable for second-life battery applications [17,61].

4.9. Comparison Table: Existing AI Models vs. Proposed Framework

Unlike most previous AI models that focus only on technical predictions, this study uniquely integrates AI-based monitoring with sustainable recycling pathways, strategic policy planning, and innovative business models. This makes the framework broader, more practical, and better suited for real-world use of second-life EV batteries, as shown in **Table 10**.

Table 10. Existing AI models vs. proposed framework.

Feature/Capability	Existing AI Models [9,62–66]	Proposed Framework
Application Scope	Focus primarily first-life EV battery monitoring [9,63–66].	Integrated first and second life battery monitoring, with adaptive parameters for degraded cells.
Data source	Limited laboratory data test datasets or EOM controlled telematic [9,64,65].	Combined real world usage survey, suggests testing in different regions and use cases.
Predictive Accuracy	80–90% accuracy in SOH prediction under controlled conditions [9,65,66].	> 90% projected accuracy (SOH) and Remaining Useful Life (RUL) estimation under diverse, real world second life conditions.
Integration with recycling	Usually not connected to recycling or only studied separately [62].	Directly connects AI monitoring with recycling and material recovery.
Policy/Business Alignment	Minimal consideration of regulatory or economic frameworks [9,63].	Integrates AI with policy suggestions and business models for real world use.
Scalability	Limited to machine learning or rule-based models [9,64,65].	Adds new tools like blockchain enabled battery passport for tracking and better recycling.
Originality	Focused only on technical or lab results [9,63,65,66].	Unique because it combines technical, environmental, and policy views into one framework.

5. End-of-Life Recycling Strategies: Post-Secondary Use

Recycling is an essential component of sustainable battery management, such that critical materials such as lithium, cobalt, and nickel are recovered [67]. Traditional recycling methods, such as pyrometallurgical and hydrometallurgical processes, continue to dominate the industry but are costly in energy and environmentally demanding [62]. Emerging methods, including direct cathode recycling and electrochemical recovery, offer sustainable alternatives by reducing energy consumption and improving material recovery efficiency [67,68].

5.1. Investigate Sustainable and Optimized Recycling Methods

Advancements in recycling technology focus on reducing waste and maximizing material recovery rates. Sustainable methods such as electrochemical separation and solvent extraction enhance material purity while minimizing chemical waste. Electrochemical separation utilizes controlled electric fields to selectively extract lithium and cobalt ions from spent battery materials. This helps in achieving higher recovery efficiencies while eliminating hazardous chemical residues [62,67]. Solvent extraction, commonly applied in hydrometallurgical processes, has been optimized to selectively recover cobalt and nickel with high purity while significantly reducing acid consumption [67]. Recent advances in closed-loop recycling methods demonstrate that direct regeneration and hydrometallurgical routes can achieve recovery efficiencies over 95% of lithium, cobalt, and nickel from used batteries. This ensures minimal environmental impact and sustainable material reuse [68].

5.2. Analyze Degradation Patterns in Used Batteries to Determine Optimal Recycling Pathways

Understanding how lithium-ion batteries degrade helps optimize recycling efficiency. Capacity fading, electrolyte decomposition, and structural electrode deterioration influence the effectiveness of recycling approaches [58, 62]. Studies show that cathode material aging, characterized by the formation of unwanted byproducts such as lithium carbonate, can drastically reduce lithium extraction efficiency [67]. Research has shown that lithium-ion batteries with NMC cathodes degrade differently compared to LFP chemistries. NMC batteries offer higher energy density but are more prone to degradation mechanisms such as lithium plating and capacity fade, whereas LFP cells demonstrate slower degradation and greater thermal stability [61]. By characterizing degradation trends, recyclers can sort and preprocess batteries more effectively, ensuring the selection of appropriate recovery pathways that optimize material yield [42,68].

5.3. Evaluate Hybrid Recycling Approaches Combining Mechanical Pre-Treatment With Selective Leaching Techniques

Hybrid approaches integrate mechanical processing, such as crushing and separation, with chemical treatments to enhance the efficiency of material extraction [62]. Selective leaching techniques allow for targeted dissolution of valuable metals, minimizing reagent use and reducing secondary waste [67]. For example, researchers at Oak Ridge National Laboratory have developed a hybrid method that pre-treats LIBs through controlled thermal decomposition. It is followed by a low-temperature acid leaching process that recovers 100% of lithium and cobalt (96% recovery of cobalt without additional chemical input) [67, 69]. Similarly, closed-loop leaching processes where leaching agents are regenerated and reused are being tested to further reduce waste generation in battery recycling [68].

5.4. Develop an Optimized Framework for the End-of-Life Management of SLBs

Establishing a comprehensive framework involves integrating AI-driven diagnostics with efficient recycling techniques. AI-powered sorting systems, such as those developed by industrial leaders, use machine learning models to assess battery health and determine the best end-of-life pathway, either repurposing or direct recycling [70]. Additionally, standardized battery passports, proposed under the European Union's Battery Regulation, provide real-time data on battery chemistry, degradation history, and previous uses. This allows recyclers to streamline sorting and processing workflows [71,72]. Countries such as Germany and Japan have implemented producer responsibility programs where battery manufacturers must ensure end-of-life recycling, further driving the adoption of closed-loop battery supply chains [73]. Expected outcomes include improved recycling efficiencies, reduced environmental impact, and enhanced integration into the circular economy. Implementing advanced recycling technologies will result in higher material recovery rates, reducing dependency on virgin raw materials and minimizing the environmental footprint of battery production [74].

Future research should explore the scalability of AI-based sorting in low-income or decentralized markets. It should examine the use of blockchain to secure and validate battery passport data. Lifecycle assessment models are also needed to evaluate the environmental and economic impacts of AI-managed recycling infrastructures across different regions.

6. Policy and Business Model Innovation for Second Life Batteries

The widespread adoption of SLBs requires well-defined policy frameworks and innovative business models that ensure economic viability and regulatory compliance [75]. Policymakers and industry stakeholders must work collaboratively to develop regulations that promote the safe reuse, repurposing, and disposal of SLBs while maintaining sustainability and economic feasibility [76]. Establishing a standardized legal framework can reduce market uncertainties and encourage investment in SLB solutions.

6.1. Policy Framework and Business Models to Accelerate SLB Adoption

The extensive adoption of SLBs can be significantly accelerated by integrating AI within supportive policy frameworks and innovative business models. Standardization efforts are essential, particularly in certifying battery health diagnostics and AI-driven monitoring systems. Establishing universal protocols for performance evaluation and lifecycle assessment will enhance trust in AI-enabled reuse strategies and foster interoperability across platforms [67]. Simultaneously, regulatory sandboxes can enable real-world deployment of AI-managed SLBs under flexible compliance conditions. They also allow for iterative development of legal and technical standards. Furthermore, expanding EPR policies to include AI-based digital twins and predictive analytics will allow manufacturers and recyclers to optimize reuse potential and minimize environmental impact [73]. Privacy and transparency regulations should also evolve to address the ethical challenges posed by AI systems handling proprietary battery data [75].

On the business front, models such as BaaS can benefit from AI by extending the lifespan of SLBs through real-time predictive maintenance and performance forecasting. Similarly, shared ownership models in microgrids and rural electrification initiatives can use AI to manage multi-user SLB systems, promoting equitable access and transparent maintenance needs. AI also enables circular economy logistics by facilitating real-time battery tracking, performance benchmarking, and condition-based routing. These will improve cost recovery and material efficiency [77]. Furthermore, successful real-world initiatives, such as Nissan's 4R Energy program, demonstrate the commercial viability of repurposing EV batteries for home energy storage. By leveraging AI to assess remaining battery life, predict user demand, and optimize charging cycles, such programs can deliver reliable and affordable energy services while reducing environmental waste [78]. Finally, AI-powered digital twins provide virtual representations of deployed SLBs. They allow firms to simulate usage and predict failure points. This capability helps extend warranties, making second-life batteries more viable and insurable in commercial contexts. By aligning AI capabilities with adaptive regulations and outcome-based business models, stakeholders can reduce market uncertainties, enhance investment attractiveness, and support long-term sustainability goals for SLB ecosystems [17,79].

6.2. Comparative Analysis of Global SLB Regulations and AI Integration Opportunities

A comparative analysis shown in **Table 11** of global battery regulations reveals that AI can act as a strategic enabler of policy harmonization and lifecycle tracking. In regions like the European Union, AI can help automate compliance with recovery quotas and manage the complexity of digital battery passports [71,75]. In the United States, AI can unify fragmented state-level data and standardize second-life evaluation. Across all jurisdictions, AI enhances traceability, predictive maintenance, and regulatory transparency, contributing to a globally scalable circular battery economy [75].

Table 11. Comparative analysis of global SLB regulation and AI Integration opportunities.

Region/Country	Regulatory Focus	Key Instruments	Challenges	How AI Can Help
European Union	Strict recycling & recovery targets	Battery Regulation (2023): Set targets of 50% lithium recovery, digital battery passports	Data tracking, lifecycle transparency, cost of compliance	AI can automate battery passport data analysis, predict EOL timing, and optimize sorting at recycling facilities [71,80].
United States	State-level, fragmented federal framework	AB 2832 (California): producer responsibility	Lack of national regulation, inconsistent tracking, market uncertainty	AI can unify data from across states, forecast reuse value, and improve decision-making in decentralized systems [75,81].

Table 11. *Cont.*

Region/Country	Regulatory Focus	Key Instruments	Challenges	How AI Can Help
Japan	Industry-led reuse & remanufacturing	4R Strategy (Reuse, Refabricate, Recycle, Reduce)	High standards but limited scalability	AI-driven diagnostics for second-life battery screening, especially in commercial-scale reuse programs like Nissan's 4R Energy [78].
India	Emerging regulatory landscape	Draft Battery Waste Management Rules	Infrastructure gaps, inconsistent battery quality	AI can support predictive diagnostics and safe reuse of SLBs in off-grid applications [82].

6.3. Best Practice for Global Implementation

The European Union (EU)'s stringent recycling targets, which mandate minimum recovery rates for lithium, cobalt, and nickel [78], present a complementary framework that other nations could emulate. This dual approach mandating environmental performance while incentivizing industrial compliance enhances both accountability and participation. The implementation of digital battery passports within the EU enables traceability across a battery's lifecycle. It supports transparent reuse, repurposing, and recycling decisions [80]. Studies have shown that digital product passports integrated with AI and blockchain technologies can significantly improve compliance monitoring, data reliability, and material recovery planning [79]. Without such a framework, fragmented state-level regulations risk inefficiencies in battery traceability and post-consumer management [81]. In India, digital compliance tools and AI-based lifecycle analytics could bridge this gap by enabling regulators and manufacturers to manage diverse battery streams more effectively [82]. Therefore, a globally harmonized policy model combining regulation, digital tools, and market incentives stands as a best practice for scaling SLB ecosystems.

7. Case Studies of Existing Commercialization Models

Several companies have successfully implemented business models that promote SLB adoption. For example, in Kenya, second-life batteries are used for affordable energy storage in off-grid schools, providing reliable electricity for lighting and educational resources [8]. This initiative demonstrates how SLBs can enhance social development while reducing energy costs in underserved communities.

In Japan, Nissan's "4R Energy" initiative repurposes EV batteries for home energy storage, extending battery life cycles and reducing household energy costs [78]. This model integrates SLBs into residential solar systems, allowing homeowners to store excess energy and optimize consumption, thus contributing to energy grid stability. By ensuring battery health tracking and performance assessment, Nissan successfully maintains battery reliability and safety for prolonged use.

Similarly, Tesla's partnership with energy providers has facilitated the integration of repurposed EV batteries into large-scale grid storage systems, enhancing renewable energy utilization [83]. By leveraging economies of scale and AI-driven battery diagnostics, Tesla has maximized the value extraction from SLBs while ensuring economic feasibility. These cases highlight the effectiveness of business models that focus on affordability, reliability, and sustainability. They illustrate that successful SLB commercialization requires strategic partnerships, digital monitoring tools, and financial incentives to enhance adoption. **Table 12** summarizes SLB initiatives undertaken by leading EV companies in the United States.

Table 12. Second life battery initiatives [78,84–90].

Company	Second-Life Battery Initiative	Stage
Tesla	Uses second-life batteries in Powerpack and Megapack for grid storage; partners with utilities for demand response.	Commercial Deployment
General Motors (GM)	Developing battery reuse strategies with Redwood Materials; plans to build closed-loop battery systems.	Pilot / Development
Ford	Exploring second-life battery use for residential and commercial energy storage; part of Ford+ circular economy model.	Pilot / Development
Rivian	Investigating reuse of EV batteries for stationary storage in off-grid communities and charging infrastructure.	Research & Development
Lucid Motors	Early-stage research into second-life applications with energy storage partners; no commercial programs yet.	Research
Nissan (U.S. operations)	Through 4R Energy (in Japan), repurposes Leaf batteries; in U.S., supports research and pilot programs for stationary storage.	Pilot/Research

Table 12. *Cont.*

Company	Second-Life Battery Initiative	Stage
Proterra	Repurposes batteries from electric buses for grid energy storage and EV charging stations.	Commercial Deployment
BMW (U.S. initiatives)	Conducts pilot projects on repurposing i3 batteries for solar energy storage and V2G systems in the U.S.	Pilot/Research

These examples were compiled based on publicly available data from company reports, press releases, and official corporate websites. Tesla, for instance, has commercially deployed SLBs in its Powerpack and Megapack systems. These are used for frequency regulation, peak shaving, improving grid resilience, reducing reliance on fossil fuels, grid storage, and utility partnerships supporting load balancing and renewable integration [84]. General Motors has partnered with Redwood Materials to develop closed-loop battery ecosystems, aiming to enhance material reuse and lifecycle sustainability [85]. Ford is piloting second-life battery applications as part of its broader Ford circular economy initiative, with a focus on residential and commercial energy storage [86].

Rivian is actively engaged in research on off-grid storage applications using retired EV batteries, while Lucid Motors is in the early research stages of SLB adoption through collaborations with energy storage partners [87,88]. Nissan, through its 4R Energy initiative in Japan, supports second-life battery projects and has begun pilot research in the U.S. market [78]. Proterra has repurposed batteries from electric buses for use in grid energy storage systems and charging infrastructure. It reflects one of the few commercialized SLB deployments among heavy-duty vehicle manufacturers [89]. Lastly, BMW has piloted second-life applications of i3 batteries for solar storage and vehicle-to-grid (V2G) systems in the United States [90].

Although the information is not drawn from peer-reviewed literature, it provides valuable insight into the commercial and technological directions of the EV industry regarding SLBs. These company-level strategies highlight emerging market pathways and support broader sustainability efforts through extended battery utility beyond primary automotive use. **Table 13** summarizes practical implementation challenges, cost barriers, and policy enforcement issues.

Table 13. Challenges, cost barriers, and policy enforcement.

Parameters	Objective 1 AI-Based Predictive Maintenance	Objective 2 End-of-Life Recycling	Objective 3 Policy and Business Model Innovations
Practical Implementation Challenges	• Domain shift between 1st-life (EV) and 2nd-life (stationary) duty cycles. • Mixed chemistries/form factors across (Original Equipment Manufacturer) OEMs • Sensor quality • Safety detection for rare failures	• Pack variability (chemistry, form, adhesives) • Discharge protocols and short-circuit risks • Unknown SoC / embedded charge • Disassembly hazards & lack of OEM tools • Process choice (pyro, hydro, direct) • Chain-of-custody tracking after multiple ownership transfers.	• Non-uniform testing and safety standards for second-life systems across regions/utilities. • Complex performance contracts • Uncertain residual value
Cost Barriers	• Extra temperature/impedance sensing • Pack-level isolation monitors • Deployment, maintenance & retraining expenses • Operational costs of false positives/negative • SCADA/BMS/EMS integration	• Hazardous shipment and insurance • Labor-intensive teardown • Expensive emissions/wastewater controls	• High financing cost (risk premiums) • Warranty & insurance (high premium) expensive • Providing delivered services (peak shaving, frequency response) adds measurement costs. • Multi-standard certification (site, grid code, fire code) expenses
Policy/ Enforcement Issues	• Data ownership disputes (OEM vs. user) • Liability for AI decision failures • Cross-border restrictions • AI may conflict with fixed maintenance schedules in permits or insurance documents	• Strict transport/storage regulations • Proof of safe discharge before processing • Risk of illegal export to informal recyclers	• Incentives/tax credits • Lack of clarity on second-life asset qualification and end-of-life obligations

8. Public Perception and Adoption Challenges of EV and Second-Life Batteries

8.1. Survey Methodology

A structured survey was conducted to assess public knowledge regarding the second life of EV batteries. The survey was administered through Microsoft Forms within Microsoft Office 365, 2024. To ensure statistical reliability, a sample size of 98 respondents was required, calculated using a 95% confidence level and a ± 5% margin of error, based on a 6.8% population proportion derived from new EV sales in 2024. The sample size was determined using the following equations:

$$n = \frac{Z^2 x \hat{P}(1 - \hat{P})}{\varepsilon^2}$$

$$n = \frac{1.96^2 * 0.068 * (1 - 0.068)}{0.05^2}$$

$$n = 98$$

The survey was distributed over a period of 21 days, primarily targeting individuals in Odessa, Canyon, and Midland, Texas, as well as university students. This survey aimed to gauge public awareness, concerns, and willingness to adopt EVs and second-life EV batteries for alternative uses. The responses indicate significant gaps in knowledge, skepticism regarding battery reuse, and key motivators that could drive broader adoption.

8.2. Finding and Analysis

8.2.1. EV Adoption and Public Concerns

The survey revealed that only 5 out of 121 respondents currently own or drive an EV, while the overwhelming majority (116 respondents) still rely on internal combustion engine (ICE) vehicles. As shown in **Figure 4**, among non-EV owners, 101 drive gasoline-powered vehicles, followed by 13 who use diesel-powered vehicles and 13 who own hybrid models. These figures reflect the ongoing dominance of conventional vehicles and suggest that EV adoption remains limited within the surveyed population, potentially due to regional infrastructure limitations and general consumer hesitancy.

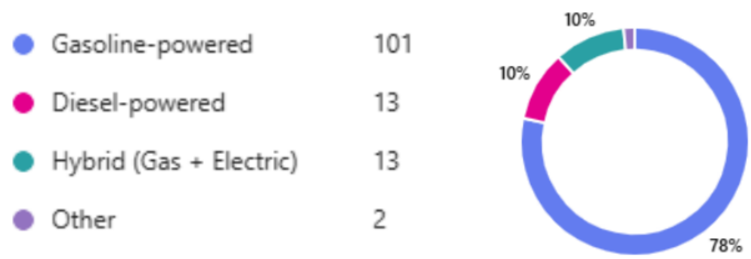

Figure 4. Type of vehicle driven by the public in Midland Texas.

Concerns about EV ownership were both widespread and consistent with national trends. A total of 86 respondents cited limited charging infrastructure as their primary concern. This was followed by 71 who expressed anxiety about battery degradation and replacement costs, and 58 who pointed to the high upfront cost of EVs as a significant barrier. Additionally, 43 respondents were concerned about the environmental impact of battery disposal, while 32 indicated uncertainty about what happens to EV batteries after use, as shown in **Figure 5**. These concerns reinforce the idea that affordability, convenience, and lifecycle transparency are major barriers to adoption.

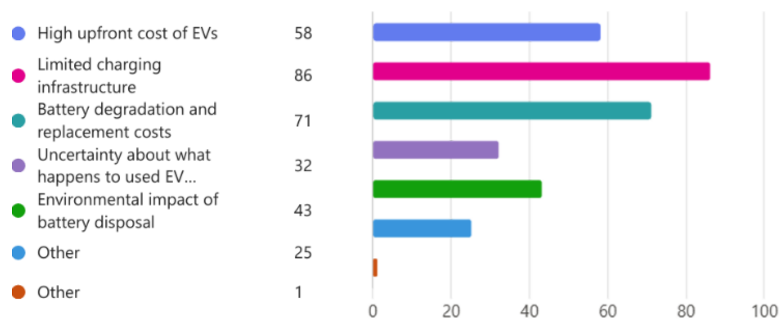

Figure 5. Primary concerns about EV ownership.

8.2.2. Awareness and Interest in Second-Life EV Batteries

The main focus of the survey was to assess public awareness regarding the potential for EV batteries to be reused after their automotive lifecycle. The data indicate a considerable knowledge gap, as shown in **Figure 6**. One hundred out of 121 respondents (approximately 83%) were unaware that EV batteries could be repurposed for applications such as home energy storage or backup power systems. This lack of awareness presents both a challenge and an opportunity, suggesting the need for public education campaigns to communicate the environmental and economic benefits of second-life battery applications. Despite limited awareness, overall interest in the concept of repurposed EV batteries was moderate. When asked to rate their interest in using second-life batteries for energy storage on a scale of 1 to 10, the average rating was 6.59. This suggests that while curiosity exists, public enthusiasm could be significantly enhanced through proper education, cost-saving incentives, and demonstrations of real-world applications.

Figure 6. Overall interest in the concept of repurposing EV batteries.

8.2.3. Trust AI-Based Battery Monitoring

Given the emerging role of AI in managing battery health and safety, the survey explored consumer attitudes toward AI-based monitoring systems. The responses were evenly distributed: 51 respondents indicated that they would trust reused EV batteries more if AI systems monitored their health and safety, 51 were unsure, and 19 expressed distrust. This level of uncertainty indicates that while AI has the potential to foster trust, hesitation remains due to concerns around transparency, reliability, or a lack of understanding of how such systems work.

Participants were also asked which AI-powered features would make them more confident in using second-life batteries. The most highly valued feature was early failure warnings, selected by 100 respondents as shown in **Figure 7**. This was followed by automatic shut-offs in the event of malfunctions (85 responses), real-time battery performance updates (81 responses), and energy efficiency tips from AI (42 responses). These findings highlight the importance of proactive safety and real-time insights, which could be critical for improving public perception of reused battery systems.

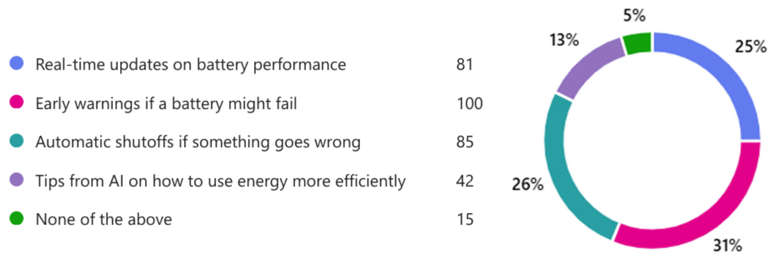

Figure 7. People's perception of AI-powered features.

8.2.4. Disposal and Recycling Preferences

When asked what should happen to EV batteries after they can no longer be reused, the majority of respondents preferred sustainable options. Sixty-seven respondents supported recycling to recover valuable materials, while 30 favored further refurbishments. Only 3 respondents indicated landfill disposal as a viable option, and 21 remained unsure, as shown in **Figure 8**. These responses suggest that the principles of a circular economy, recycle, refurbish, and repurpose, are well-aligned with public values, although some uncertainty remains due to limited information on available programs.

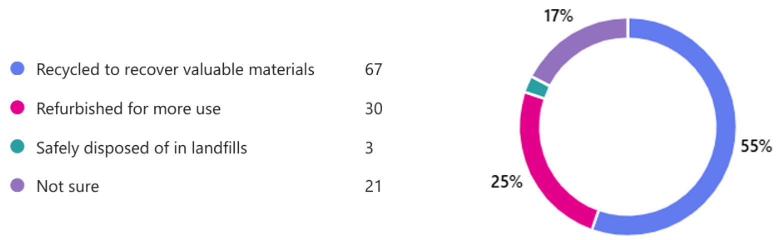

Figure 8. People's opinion about disposal and recycling.

The survey also explored what would motivate participants to recycle second-life EV batteries properly. Manufacturer buyback programs were the top motivator, with 96 respondents in favor, followed closely by financial incentives, like cashback or discounts (95 responses), and easy-to-find drop-off locations (90 responses), as shown in **Figure 9**. In contrast, only 29 respondents cited government recycling rules as a meaningful motivator. These results indicate that voluntary, consumer-centered strategies are likely to be more effective than regulatory enforcement in driving environmentally responsible behavior.

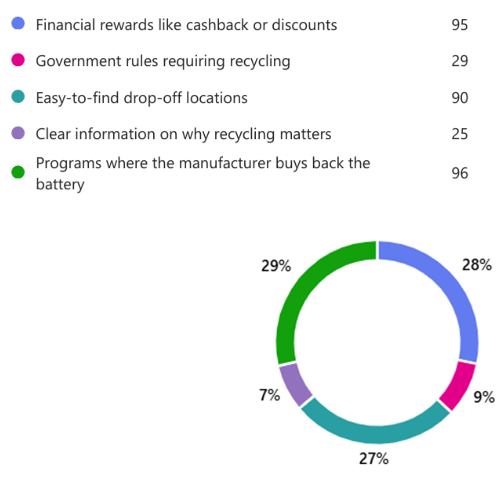

Figure 9. People's motivation to recycle EV batteries.

Regarding the willingness to pay a small fee at the time of EV purchase to support future battery recycling, 20 respondents said yes, 27 said no, and the majority (74 responses) said it would depend on the cost. This reflects a high degree of cost sensitivity and reinforces the importance of transparent pricing and clear value propositions in implementing any policy or business model.

8.2.5. Business Model for Second-Life Battery Adoption

Understanding consumer preferences for different business models is essential to developing a market for second-life EV batteries. When presented with options, 50 respondents preferred full ownership with maintenance support from the manufacturer, while 49 favored a pay-per-use model. Only 18 respondents selected the BaaS model, and just 3 favored a monthly subscription-based lease, as shown in **Figure 10**. These responses suggest a clear preference for ownership and flexible, usage-based approaches over long-term leasing models or subscription services.

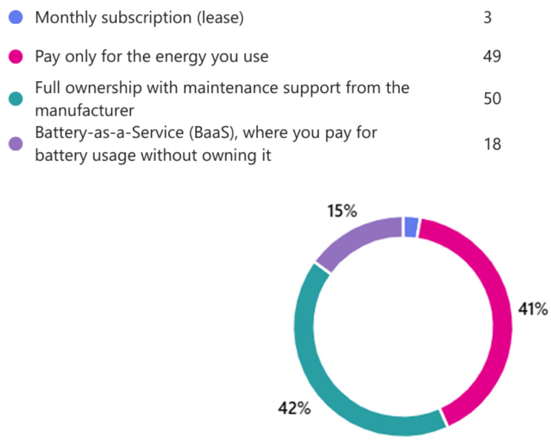

Figure 10. Business models' interest in second-life batteries.

When asked whether governments should mandate companies to reuse or repurpose EV batteries before disposal, 60 respondents supported the idea, 36 were unsure, and 24 opposed it. Among various policy incentives, tax discounts for users of second-life batteries emerged as the most appealing option, favored by 75 respondents, as shown in **Figure 11**. Other options like financial support for companies (19 responses), stricter disposal regulations (14), and public awareness campaigns (13) were less popular, indicating that direct economic benefits for consumers are more influential than institutional or regulatory actions.

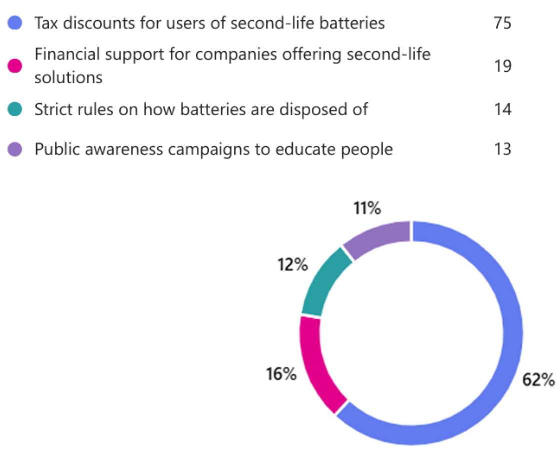

Figure 11. Policy incentives.

8.2.6. Concerns and Market Outlook

Despite moderate interest and favorable views of AI, several concerns continue to hinder the wider acceptance of second-life EV batteries. The most cited concern was safety risks such as fire hazards, selected by 47 respondents. Uncertainty about battery lifespan (24 responses), lower performance compared to new batteries (21 responses), and insufficient information about second-life uses (24 responses) were also commonly mentioned, as shown in **Figure 12**. This highlights the importance of addressing both technical challenges and consumer perceptions related to safety and durability in order to facilitate market acceptance and growth of second-life EV batteries.

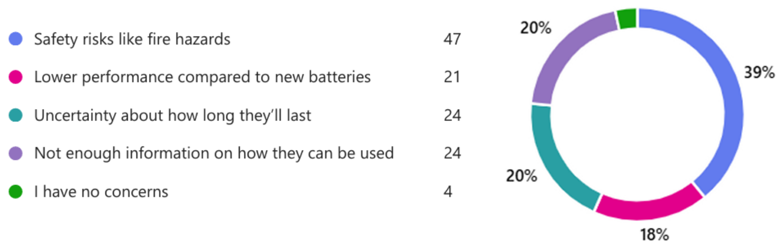

Figure 12. Concerns about second-life EV batteries.

Looking forward, public opinion is mixed regarding the adoption of second-life batteries as a mainstream solution for renewable energy storage. Only 32 respondents believed that such batteries would become common in the next decade, while 24 disagreed and 65 were unsure. However, when asked if they would choose a second-life battery over a new one if AI could ensure 90% of the original performance, 86 respondents said they might, depending on potential cost savings, and 26 said they would definitely choose it. Only 9 respondents indicated they would not consider it. These responses reveal that demonstrating economic value combined with validated performance and safety assurances could be decisive in driving adoption.

The survey reveals both challenges and opportunities for the adoption of second-life EV batteries. While awareness is low, interest is promising when safety and cost benefits are demonstrated. AI-powered safety features, financial incentives, and consumer-centered business models appear key to building trust. Policies should prioritize education, performance transparency, and convenience. With proper support, second-life batteries can make a meaningful contribution to sustainable energy strategies and circular economy goals.

9. Conclusions

The increasing proliferation of EVs has accelerated the urgency of addressing the challenges and opportunities posed by end-of-life battery management. This study explored a comprehensive framework for advancing second-life EV battery applications through three critical perspectives: AI-based predictive maintenance, sustainable recycling strategies, and policy and business model innovations. Collectively, these elements form a synergistic approach that enhances battery lifecycle value, supports circular economic objectives, and promotes environmental sustainability.

AI-based predictive maintenance emerged as a transformative tool in battery health diagnostics and lifecycle extension. Unlike traditional empirical approaches, AI-driven models such as LSTM networks and Gaussian Process Regression enable real-time monitoring, early fault detection, and precise degradation forecasting. These capabilities reduce operational risks, optimize battery reuse potential, and enhance energy efficiency across diverse second-life applications, including stationary storage and grid support systems.

Simultaneously, the study highlighted the limitations of existing recycling infrastructures and emphasized the need for next-generation recycling technologies. Techniques such as electrochemical separation, solvent extraction, and hybrid mechanical-leaching processes provide more sustainable alternatives. They also achieve higher yields than conventional pyrometallurgical and hydrometallurgical methods. Integrating AI with recycling operations enhances sorting precision, process selection, and material recovery, thereby reducing environmental impact and conserving critical resources like lithium, cobalt, and nickel.

Policy frameworks and business models represent the third component of scalable second-life battery adoption. Instruments such as battery passports and EPR regulations improve lifecycle traceability and accountability. Business models like BaaS, leasing, and manufacturer buyback programs offer economically viable options for consumers and enterprises while incentivizing responsible end-of-life practices. Comparative analysis of global policies further underscores the value of combining regulatory mandates with market-based incentives.

Public perception, as captured through the survey, reveals that while awareness of second-life battery potential remains limited, interest is growing, particularly when safety, performance, and cost savings are assured. Trust in AI-powered systems and a preference for consumer-friendly policy incentives (e.g., tax discounts, buyback programs) highlight the importance of transparency, education, and user-centered design in promoting widespread adoption. In conclusion, the integration of intelligent monitoring, advanced recycling, and progressive policy strategies offers a robust pathway for the sustainable management of second-life EV batteries. These approaches not only mitigate environmental risks and resource constraints but also unlock new economic and social value across energy and mobility sectors. To fully realize this potential, continued interdisciplinary research, stakeholder collaboration, and public engagement are essential. By aligning technological innovation with systemic support structures, second-life batteries can play a pivotal role in shaping a resilient and sustainable energy future.

While this study provides a comprehensive overview and proposes a novel framework, several limitations must be acknowledged. First, the analysis draws primarily on published research and industry reports, which may not capture the most recent proprietary data or emerging pilot projects on SLBs. Second, although AI-based maintenance strategies are discussed in light of current evidence, their scalability and robustness in real-world, large-scale deployments remain uncertain. Third, the proposed policy and business model recommendations are presented at a general level and may require significant adaptation to account for country-specific regulatory environments, infrastructure readiness, and market conditions. Finally, while the suggested recycling methods are supported by recovery data, their feasibility and cost-effectiveness in resource-constrained regions or smaller community contexts remain untested.

Future research should prioritize field validation of AI-powered battery management systems through pilot projects across diverse geographies and application domains. Comparative assessments of environmental, social, and economic impacts are also needed to establish cost–benefit trade-offs and long-term sustainability. Policy design should integrate both regulatory measures and incentive mechanisms to accelerate adoption while ensuring equity across different markets. Emerging tools such as blockchain-enabled digital "battery passports" combined with AI-driven sorting could enhance transparency, traceability, and efficiency in recycling pathways. Ultimately, the successful implementation of this framework requires interdisciplinary collaboration among engineers, policymakers, economists, and environmental scientists to bridge the gap between conceptual innovation and scalable, real-world deployment.

Author Contributions

Conceptualization, M.N.B., A.S.S., and V.H.S.; methodology, M.N.B., A.S.S., and V.H.S.; software, M.N.B.; validation, M.N.B.; formal analysis, M.N.B. and A.S.S.; investigation, M.N.B.; resources, M.N.B. and A.S.S.; data curation, M.N.B.; writing—original draft preparation, M.N.B.; writing—review and editing, J.P. and V.H.S.; visualization, J.P. and V.H.S.; supervision, A.S.S., J.P., and V.H.S.; project administration, A.S.S., J.P., and V.H.S. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Verbal informed consent was obtained from the participants. Verbal consent was obtained rather than written because (1) participation was voluntary and low-risk, (2) all data were collected anonymously without identifying information, and (3) requiring written consent could have reduced the number of participants. No identifying information was obtained; therefore, a signed consent form was not required.

Data Availability Statement

The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest

The authors declare that there is no conflict of interest.

Abbreviations

AB	Assembly Bill
AI	Artificial Intelligence
APC	Article Processing Charge
BMS	Battery Management System
CAGR	Compound Annual Growth Rate
CATL	Contemporary Amperex Technology Limited
CC	Creative Commons
CL	Conductivity Loss
EIS	Electrochemical Impedance Spectroscopy
EOL	End of Life
EPR	Extended Producer Responsibility
ESS	Energy Storage System
EU	European Union
EV	Electric Vehicle
GPR	Gaussian Process Regression
ICE	Internal Combustion Engine
IEA	International Energy Agency
IEEE	Institute of Electrical and Electronics Engineers
LAM	Loss of Active Material
LD	Linear Dichroism
LFP	Lithium Iron Phosphate
LLI	Loss of Lithium Inventory
LSTM	Long Short-Term Memory (neural network)
ML	Machine Learning
NMC	Nickel Manganese Cobalt (battery chemistry)
ROI	Return on Investment
RUL	Remaining Useful Life
SEI	Solid Electrolyte Interphase
SLB	Second-Life Battery
SOC	State of Charge
SOH	State of Health

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